The Impact of Credit Information Sharing in Banking Sectors

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Abstract

This thesis provides an analysis of the economic consequences of information sharing among banks about information on their borrowers, so-called "Credit Information Sharing". Particularly, our research objectives are to assess the impact of credit information sharing on bank lending, bank risk, and bank-specific stock price crash risk. Our main data sources include the Bankscope database, Datastream, IFRS Foundation website, Deloitte, the World Bank's Doing Business database, the World Bank's World Development Indicators database (WDI), the World Bank's Global Financial Development database (GFDD), the World Bank's Banking and Supervision Survey database. Our sample consists of banks around the globe during the period of 2005-2013. For the empirical investigation throughout the thesis, we employ a panel model and perform bank fixed (within) effects estimation augmented with time dummies. In addition, we provide several robustness tests, which include alternative measures, additional controls, a subsample analysis and an instrumental variable approach.

In chapter 2, we investigate the impact of credit information sharing on bank lending for 16,009 banks in 113 countries during 2005-2013 and the finding shows that bank lending increase with more credit information sharing. In addition, by assessing two–way interactions in the regression, we find that such impact is less pronounced with more transparent information environment and stronger creditor protection. In chapter 3, we examine the impact of credit information sharing on bank risk for 15,558 banks in 105 countries during 2005-2013 and we discover that more credit information sharing reduces bank risk. Moreover, by evaluating two-way interactions in the regression, the finding reveals that such impact is less pronounced with more transparent information environment and more pronounced with more competitive banking markets. In chapter 4, with the sample of 1,402 listed-banks in 55 countries during 2005-2013, we explore the impact of credit information sharing on bank-specific stock price crash risk and the result notably shows that more credit information sharing via public credit registries has a negative impact on a stock price crash risk. Furthermore, by considering two-way interactions in the regression, such impact is less pronounced with more transparent information environment and more pronounced with weak regulatory environments in banking sectors.

Our findings suggest that policymakers should strive to achieve effective and efficient credit information sharing schemes to promote healthy and well-functioning banking sectors. As information sharing bridges the information gap between banks and their borrowers, banks are thus willing to extend more credit. Not only enhancing credit availability, banks become more stable and less likely to hoard negative information with a greater degree of credit information sharing.

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Declaration

No part of this thesis has been submitted elsewhere for any other degree or qualification in this or any other university. It is all my own work unless referenced to the contrary in the text.

Statement of Copyright

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Chapter 1: Introduction

1.1 Credit Information Sharing

Banking sectors are essential for countries at all stages of development and in all parts of the world (Levine 2005; Barth *et al.* 2009). When banks operate efficiently and allocate savings to the most productive investment, it enhances the performance of economies and stimulates economic growth (Levine 2005). Since bank lending is a source of external finance, especially in developing and emerging countries, a well-functioning banking system can help overcome income inequality and poverty. Thus, the functioning of banks has ramifications for the operations of firms and the prosperity of nations (Levine 2004).

Unfortunately, banking systems do not allocate funds efficiently because they usually face information problems. Asymmetric information between banks and borrowers have long been the main issue in credit markets discussed by analysts and policymakers (Stigler 1961; Stiglitz & Weiss 1981). Generally, major roles of banks are to acquire information about borrowers and establish lending relationships with them to overcome asymmetric information in credit markets (Diamond 1991; Rajan 1992; Freixas & Rochet 2008). A striking feature of banks is their services that they offer and the economies of scope between them. For example, accounts and payments' services provide banks valuable data on the creditworthiness of clients as potential borrowers. A consumer who receives a regular paycheck pays credit cards in full and those and other bills on time is normally considered as a better credit risk than one that does not.

Both banks and borrowers possess different information about the risk of default, so banks are usually exposed to the problem of asymmetric information. The problem of asymmetric information between banks and borrowers can generally be classified as adverse selection and moral hazard. The adverse selection problem arises when individuals and firms seek out for loans. These clients have better information about its financial state and its ability and willingness to repay the loan than their lenders. When individuals and firms apply for loans, banks thus are not able to observe the true underlying characteristics and creditworthiness of them. Thus, it is difficult for banks to differentiate between good (safe) and bad (risky) loan applicants (Akerlof 1970; Stiglitz 1985). Moreover, the moral hazard problem takes place after a loan is granted. Borrowers may use loaned funds to spend in ways that are not agreed upon or inconsistent with the interest of the banks. When banks are poorly informed about borrowers' characteristics and post-lending actions, market failure is likely. Stiglitz and Weiss (1981) show that under asymmetric information the demand for loanable funds exceeds the supply at the market equilibrium – even borrowers are willing to pay the market equilibrium interest rate are not able to get a loan (credit rationing).

To alleviate the problems caused by asymmetric information, banks usually engage in screening and monitoring of borrowers. For instance, they can interview loan applicants, visit their business before and after granting loans, and gather information from public records (Jappelli & Pagano 2002). If banks operate on a large scale, they can use these data for statistical risk management to grant and price loans based on past performance. Furthermore, collateral is commonly used as one of the tools to reduce asymmetric information (Bester 1985; Besanko & Thakor 1987). However, this requires that the borrowers have sufficient pledge-able assets or else they will not receive loans. Collateralization of loans is also often problematic especially for new firms, micro-entrepreneurs and small-medium enterprise, which often lack fixed assets to present as collaterals. Thus, the use of collaterals is not able to fully solve the problems resulting from asymmetric information. Another remedy for banks, however, is to share with other banks information on their borrowers. Formal information sharing takes place through privately held credit bureaus and publicly regulated credit registries. Such credit information sharing institutions disseminate knowledge of total debt exposure, payment history, and overall creditworthiness, thus bridging the information gap between banks and borrowers.

The theoretical literature suggests that there are four different mechanisms through which credit information sharing can alleviate the asymmetric information problem in lending. First, credit information sharing improves the knowledge of loan applicants' characteristics so that banks can differentiate between safe and risky borrowers, reducing the problem of adverse selection (Pagano & Jappelli 1993). In the absence of credit information sharing, banks cannot distinguish between new pools of potential borrowers who are likely to repay and those who are likely to default. Since new loan applicants might have borrowed from other banks in the past, credit information sharing among banks can, therefore, help banks grant loans safely. However, the effect of credit information sharing on the volume of lending is still not clear-cut. On one hand, credit information sharing increases the volume of bank lending when the problem of adverse selection in the absence of information sharing is so severe that safe borrowers are priced out of the market. On the other hand, credit information sharing decreases the volume of bank lending when safe borrowers participate in the credit market even in the absence of credit information sharing. The overall impact of credit information sharing on bank lending depends upon the extent to which increase lending to safe borrowers compensates for the reduction of lending to risky borrowers.

Second, credit information sharing reduces the information monopoly a bank has on its borrowers (Sharpe 1990; Padilla & Pagano 1997). As banks acquire private information about their borrowers within their lending relationship, they have information advantage that allows them to charge higher interest rate from borrowers in the future, generating a hold-up problem (borrowers are held up in one bank). With high-interest rate, borrowers exert less effort to repay and end up default, potentially leading to the collapse of credit market (Keeley 1990). When banks commit to sharing credit information among other banks, the extraction of information rents is restrained and in turn induces borrowers to step up their effort level to repay, reducing default rate. As a result of reducing default, interest rate decreases and bank lending in turn increases.

Third, the information sharing mechanism exerts a disciplinary effect on borrowers by encouraging them to perform and maintain a good reputation because the information about their defaults is shared among other banks (Klein 1992; Vercammen 1995; Padilla & Pagano 2000). Credit information sharing encourages borrowers to repayment because it allows borrowers who default to be blacklisted. As blacklisted, borrowers may have difficulty getting credit in the future. To avoid this penalty, borrowers have the incentive to exert more effort, leading to lower default and interest rates and to more bank lending. However, as shown by Padilla and Pagano (2000), sharing merely information about a default has a potential impact on increasing bank lending; sharing information borrowers' quality may not increase bank lending. This is because when sharing information sharing about defaults only, high-quality borrowers try harder to avoid default as to avoid being pooled with low-quality borrowers by outside banks. When banks share information more than just default, the high-quality borrowers exert less effort to avoid default because they know that the bank will disclosure not only information about default but also the information about their intrinsic quality. Because information sharing eliminates information rents in the future; however, banks require a higher probability of repayment to be willing to lend and they may choose to refrain from lending altogether.

Finally, credit information sharing among banks prevents over-borrowing which arises in the case of multiple bank lending (Bennardo *et al.* 2014). Borrowing from several banks induces borrowers to behave opportunistically by over-borrow from each bank. In such situation, banks may extend credit to already indebted people or firms. This multiple lending can thus cause a negative externality among banks because each bank's lending may increase default risk for other banks. To prevent over-borrowing, banks' natural response is to ration credit. Banks can also response by committing to share credit information among other banks. Credit information sharing allows banks to assess the outstanding debts of each borrower and adjust loan offers to applicants' credit exposure so that banks can lend safely. With credit information sharing, banks no longer need to ration credit and charge higher interest rate; therefore, bank lending increases with credit information sharing.

1.2 Motivation

The impact of credit information sharing on bank lending is still ambiguous according to theoretical perspectives. The total change in lending depends on the force between the increase in lending to safe borrowers and the decrease in lending to risky borrowers. There are a few empirical studies exploring the impact of credit information sharing on bank lending, and they agree that bank lending increases with more credit information sharing (Jappelli & Pagano 2002; Djankov *et al.* 2007; Brown *et al.* 2009).

Nevertheless, the literature still lacks the empirical evidence on the bank-level lending (supply side) evidence. Thus, in chapter 2, we aim to investigate the impact of credit information sharing on bank lending by providing an updated bank-level data around the globe. Specifically, we attempt to answer this question "How, and to what extent, credit information sharing affect the volume of bank lending?". We rely on bank-level data to ensure that individual banks' reactions to credit information sharing are not confounded by aggregate variation in credit allocation. Also, bank-level data helps to isolate variations in credit allocation arising from the heterogeneity of banks. Furthermore, studying the supply side of bank lending is an approach consistent with theoretical analyses of information sharing in the credit market (Pagano & Jappelli 1993; Padilla & Pagano 1997, 2000; Bennardo *et al.* 2014).

According to the theoretical literature, the effect of credit information sharing on the volume of bank lending depends on the severity of the asymmetric information between banks and borrowers. When the information environment is more transparent, more borrower information should be available and accessible to the public, such that the asymmetric information between banks and borrowers is less problematic. Therefore, in chapter 2, we examine whether the effect of credit information sharing on bank lending varies with the transparency of the information environment. In more transparent information environment, the impact of credit information sharing on bank lending should be less pronounced.

In some circumstances, the asymmetric information between banks and borrowers may not be problematic. When banks are well protected in the event of default, they can easily force repayment, grab collateral, or even gain control of the firm (Townsend 1979; Aghion & Bolton 1992; Hart & Moore 1994, 1998). Thus, banks may be willing to extend more credits, regardless of the severity of the asymmetric information. In this regard, in chapter 2, we also examine whether the effect of credit information sharing on bank lending varies with the level of creditor protection through the legal system. The effect of credit information sharing on bank lending should be less pronounced with a high level of creditor protection.

While the empirical analysis of chapter 2 is interesting, they lead to a very important issue about the economic consequence of credit information sharing on bank risk. Although credit information sharing facilitates bank lending decision and encourages banks to provide more credit, it does not always produce a positive repercussion on the stability of banking systems. From a positive perspective, the expansion of credits to a broader range of borrowers enhances overall economic growth. From a more negative perspective, an increase in lending may lead to greater access to credit for riskier borrowers. The disproportionally high entry of risky borrowers may lead to deteriorated bank portfolios with higher default rates. The high entry of risk borrowers may lead to increasing bank risk and probability of banking crises. Therefore, in chapter 3, we attempt to explore the consequences of credit information sharing on bank risk.

In theory, there is a link between credit information sharing and bank risk. The theory predicts that credit information sharing may decrease bank risk. Specifically, credit information sharing can reduce adverse selection (Pagano & Jappelli 1993), increase borrowers' effort to repay their debts (Padilla & Pagano 1997, 2000), and prevent excessive lending when each borrower may patronize several banks (Bennardo *et al.* 2014). Thus, credit information sharing should reduce default probability and translate into lower bank risk. However, the theory also predicts that credit information sharing may lead to looser screening requirements and lower level of post-lending effort in monitoring (Dell'Ariccia & Marquez 2006), contributing to rapid credit expansion and lending to riskier borrowers. Therefore, credit information sharing may increase bank risk.

Like chapter 2, the impact of credit information sharing on bank risk may vary with the transparency of the information environment. Thus, in chapter 3, we also investigate the impact of information environment on the relationship between credit information sharing and bank risk. In comparison to less transparent information environment, credit information sharing should have a weaker effect on bank risk in a more transparent information environment. The asymmetric information becomes less severe with more transparent information environment, such that promoting information sharing among banks may be less helpful in reducing bank risk.

Despite the focus of academic and policy debate on the impact of banking competition on bank risk (Allen & Gale 2004; Berger *et al.* 2009; Agoraki *et al.* 2011; Fernández *et al.* 2016), there is a potential interaction effect between credit information sharing and banking competition that could influence the level of bank risk. In competitive banking markets, adverse selection and moral hazard problems (associated with borrowers) is more intense compared to less competitive banking markets (Shaffer 1998; Dell'Ariccia 2001; Marquez 2002). Banks in competitive banking markets have less incentive to screen and monitor borrowers after lending. Failure to adequately screen and monitor leads to riskier portfolios and weaker balance sheets with potentially negative effects on bank stability (Dell'Ariccia & Marquez 2006). With the role of credit information sharing in reducing adverse selection and moral hazard problems, its impact on bank risk could be more pronounced in banking markets with a high degree of competition. To date, the interaction effect of credit information sharing and banking competition on the level of bank risk has never been tested before. Thus, in chapter 3, we also examine the impact of banking competition on the relationship between credit information sharing and bank risk.

In Chapter 3, we examine the effect of credit information sharing on bank risk basing on the asymmetric information between banks and borrowers. In contrast, Chapter 4 attempts to explore a different type of risk which arises from the asymmetric information between banks and outside investors. This type of risk refers to downside risk or the risk of extreme losses. It is the ability of banks to make loans that cause banks to be opaque to outside investors. When banks make loans, they possess private information about borrowers, and the credit quality of borrowers is not readily observable and accessible by outside investors. This opacity enables corruption in lending and provides lending officers opportunities to conceal any bad projects or adverse operating outcomes for an extended period. Eventually, the unanticipated release of accumulated negative information may lead to the risk of extreme losses, namely crash risk.

Since the 2008 financial crisis, the concern of crash risk has been increasing. In the onset of the crisis, investors' lack of confidence and fear of further decreases in prices have been identified among the various culprits behind the sharp price declines (Kim *et al.* 2013). Crash risk is an essential characteristic of return distribution and captures asymmetry in risk, especially downside risk or extreme negative return. Hence, it is important for portfolio theories, asset-pricing and option-pricing models (Kim *et al.* 2014; Kim & Zhang 2015). Unlike the risks from symmetric volatilities, crash risk is the risk of extreme losses which cannot be reduced through portfolio diversification (Mitton & Vorkink 2007; Barberis & Huang 2008; Sunder 2010; Kim *et al.* 2011b; Conrad *et al.* 2013).

Previous studies show that there are several mechanisms that could generate crash risk. These mechanisms are referred to leverage effects (Black 1976; Christie 1982), investor heterogeneity (Romer 1993; Hong & Stein 2003) and volatility feedback effects (French *et al.* 1987; Campbell & Hentschel 1992). However, our study in Chapter 4 relies on another factor that increasingly captures much of attention in the crash risk literature. This factor is the information opacity that provides corporate managers incentives to conceal bad news (negative information) from outside investors (Jin & Myers 2006; Hutton *et al.* 2009).

According to the information theory of Jin and Myers (2006), the asymmetric information between corporate insiders and outside investors/stakeholders provides corporate directors, officers or employees an incentive to hide bad news. A wide range of incentives, such as compensation contracts, career concerns, and empire building, motivate managers to hide unfavorable outcome from their poor performance (Ball 2009; Kothari *et al.* 2009). If an insider conceals bad news (negative information) for an extended period, a firm's share price may be overvalued, creating a bubble. When the bad news accumulates and reaches its upper limit, that bad news will be suddenly released to the stock market all at once. Consequently, the bubble bursts and a stock market crash (Jin & Myers 2006; Hutton *et al.* 2009). More importantly, hiding bad news prevents investors and board of directors to take an early action to correct or liquidate bad projects. As a consequence, unprofitable projects are kept alive and their poor performances pile up over time until a collapse of asset price occurs (Bleck & Liu 2007).

As argued by Hertzberg *et al.* (2010), the incentive of hiding bad news is due to a loan officer's career concern. Due to career concern, a loan officer tends to hide information about their assigned borrower's repayment prospect that reflects poorly on their own report. This hidden negative information eventually prevents investors and the board of directors from taking timely abandonment actions or discerning negative net present value (NPV) projects at an early stage (Bleck & Liu 2007).

Due to potentially bad news hoarding behaviors, we argue that credit information sharing among banks about their borrowers' creditworthiness will discourage bank loan officers to engage in bad news hoarding behaviors and subsequently lead to a reduction in stock price crash risk. We base on our prediction on these following reasons. First, credit information sharing helps to monitor loan officers and to prevent corruption in lending. Second, sharing of borrowers' information from one bank will be beneficial to another bank's manager validating internal risk ratings and will prevent loan officers from being bias in their reports about borrowers. Third, credit information sharing improves comparability that discourages bad news hoarding within banks. Thus, more credit information sharing can improve bank transparency and help to curb bad news hoarding activities of loan officers. Consequently, the perception of investors about banks' true underlying performance is improved and the risk of stock price crash is suppressed. Our prediction has never been tested before so it is left to empirical investigation. Therefore, in chapter 4, we attempt to examine the impact of credit information sharing on stock price crash risk.

Nonetheless, how relevant would a credit information sharing scheme be if information environment was hardly opaque? This question leads to another attempt in chapter 4. In an environment with more transparent information environment, loan officers may have less ability to hide negative information because more information is accessible to external investors and loan managers. Therefore, in chapter 4, we examine whether the impact of credit information sharing on crash risk varies with the transparency of the information environment.

Furthermore, the banking industry is known to be heavily regulated by regulators and authorities because they play an essential role in channeling savings to the most productive investment projects and thereby enhance the performance of economies (Barth *et al.* 2004; Levine 2004, 2005). Regulation and supervision are considered as an additional external governance force that acts macroeconomically at the banking industry level and microeconomically at the individual bank level (Barth *et al.* 2006; Beck *et al.* 2006b; De Andres & Vallelado 2008). When the banking regulatory environment is strict, banks are less likely to have enormous discretion to act in their own interests rather than in the interests of shareholders and debt holders. In addition, if banks face strict regulatory environments, they are more likely to allocate capital efficiently and have less ability to conceal bad news. Thus, in chapter 4, we also attempt to examine whether the impact of credit information sharing on crash risk depend on the strictness of the banking regulatory environments.

To sum up, our objectives in Chapter 2 are to examine the impact of credit information sharing on bank lending and explore whether such impact varies with the transparency of the information environment and the level of creditor protection. Our objectives in Chapter 3 are to investigate the impact of credit information sharing on bank risk and analyze whether such impact varies with the transparency of the information environment and the level of banking competition. Our objectives in Chapter 4 are to examine the impact of credit information sharing on bank-specific stock price crash risk and explore whether such impact varies with the transparency of the information environment and the banking regulatory environments.

1.3 Findings and Contribution

Using a cross-country sample of 16,009 banks in 113 countries during the period of 2005 to 2013, the findings in chapter 2 reveal that credit information sharing and bank lending are positively associated. This finding is consistent with theoretical analyses suggesting that credit information sharing promotes bank lending. Our results also show that improved transparency of information environment mitigates the impact of credit information sharing on bank lending. Furthermore, we find that credit information sharing only affects bank lending through its interaction with credit rights. Specifically, credit information sharing reduces bank lending in countries with strong creditors rights, while it has no notable effect on lending in countries with very weak creditor rights.

Chapter 2 contributes to the existing literature in the following ways. First, we contribute to the emerging literature on information sharing in credit markets. We examine how information sharing impacts the volume of bank lending an effect ambiguous in theory and underexplored empirically. Specifically, we provide empirical evidence on the supply side of bank lending, which is still scarce. Unlike country-level data, bank-level data ensures that individual banks' reactions to credit information sharing are not confounded by aggregate variation in credit allocation. In particular, bank-level data helps to isolate variations in credit allocation arising from (unobserved) heterogeneity of banks. In addition, because we utilize bank-level data, as opposed to firm-level data (Brown *et al.* 2009), we are able to study the determinant of bank lending volume from the banks' viewpoint, an approach consistent with theoretical analyses of information sharing in the credit market (Pagano & Jappelli 1993; Padilla & Pagano 1997, 2000; Bennardo *et al.* 2014).

Second, we employ the IFRS adoption as a proxy of transparency of information environment and provide evidence that the beneficial effect of credit information sharing on bank lending is lessened with the mandatory IFRS adoption. Our findings support the role of IFRS in enhancing transparency of information environment and increasing the comparability of financial reports. Third, we complement Djankov *et al.* (2007) and find that creditor protection through the legal system is complementary to credit information sharing. Strong creditor protection is necessary to guarantee the effect of information sharing on lending.

Last, we use bank-level lending and more comprehensive measures of credit information sharing to revisit the cross-country association between credit information sharing, creditor rights, and bank lending. In general, previous cross-country studies (Jappelli & Pagano 2002; Djankov *et al.* 2007) only consider a dummy equals to one if any information sharing institution operates in the country, and zero otherwise. However, our study employs more comprehensive measures of credit information sharing from the World Bank's Doing Business, which takes into account the scope, coverage, and accessibility of credit information available through either a private credit bureau or a public credit registry. In addition, we provide alternative measures of credit information sharing with private credit bureau coverages (% of adult population) and public credit registry coverages (% of adult population) to measure the level of credit information sharing through each agency.

Using a cross-country sample of 15,558 banks in 105 countries during the period of 2005 to 2013, our findings in chapter 3 reveal that credit information sharing is negatively associated with bank risk. This finding suggests that bank risk is lower in countries with more credit information sharing. Our result rules out the prediction of increasing bank risk, which may be due to looser screening requirements and lower level of banks' post-lending effort in monitoring. The results in chapter 3 also show that the negative relationship between credit information sharing and bank risk is less pronounced in an information environment with a greater level of transparency. When the information environment is more transparent, borrower information is abundantly available and accessible to the public, such that promoting credit information sharing may be less helpful in reducing bank risk. Furthermore, in more competitive banking markets, credit information sharing is more beneficial in reducing bank risk than less competitive markets. In other words, the impact of credit information sharing on bank risk is more pronounced in more competitive banking markets.

Chapter 3 adds to the existing literature in several aspects. First, we revisit and investigate the impact of credit information sharing on bank risk by using a wider range of countries around the globe. While Houston *et al.* (2010) provide an analysis of bank risk in 69 countries, we expand the analysis to banks in 105 countries. Second, in addition to using bank Z-score index for gauging the level of bank risk, we also rely on another indicator of bank risk, which is a ratio of non-performing loans to total loans (NPL). While the Z-score index measures the overall bank-risk and likelihood of failure, the ratio of non-performing loans to total loans reflects the quality of the loan portfolio, reflecting the credit risk position of a bank (Berger *et al.* 2009; Delis & Kouretas 2011).

Last, we add to the literature on information sharing and bank stability on one hand and the literature of banking competition and bank stability on the other hand. We demonstrate that there are significant and interactive effects of credit information sharing and banking competition. Far from having a neutral effect, we show that they have a profound influence on the level of bank risk. Our findings suggest that a credit information sharing scheme is more beneficial in a banking market characterized by high degree of competition.

Using a cross-country sample of 1,402 listed-banks in 55 countries during the period of 2005 to 2013, our findings in Chapter 4 indicate that credit information sharing through public credit registries reduces bank-specific stock price crash risk, whereas the depth of credit information sharing and information sharing through private credit bureaus have no significant effect on crash risk. These findings reveal that banks in a country with more information sharing through public credit registries are less likely to experience crash risk. These findings are consistent with our conjecture that credit information sharing may prevent banks' loan officers from concealing and accumulating bad news, which could lead to a future stock price crash. The insignificant impact of information sharing through private credit bureaus on crash risk suggests that the voluntary exchange of credit information among banks may not be sufficient to prevent bad news hoarding. Banks may self-select themselves into sharing credit information and may share only information that makes them better off. In addition, joining the private credit bureaus is not compulsory and they are less regulated than the public credit registries (Majnoni *et al.* 2004). Thus, less transparent banks may not join credit bureaus to share borrower information in the first place.

Moreover, we find that the impact of credit information sharing on crash risk is less pronounced with more transparent information environment. With more transparent information environment, bank loan officers have less ability to conceal negative information about borrowers because more information is assessable to both investors and loan managers. Furthermore, according to three aspects of bank regulations, we find that the impact of credit information sharing on crash risk is more pronounced with less stringent capital requirements, low supervisory power and low degree of private monitoring. Our results suggest that credit information sharing is much more helpful in reducing crash risk when the regulatory environments are weak, especially when the supervisory power is low.

Chapter 4 contributes to the existing literature in several dimensions. First, our study adds to the growing literature on banks' credit information sharing and its economic consequences. Prior works in this area has studied the impact of credit information sharing on enhanced credit availability (Pagano & Jappelli 1993; Padilla & Pagano 1997; Djankov *et al.* 2007; Brown *et al.* 2009), in lowering cost of credit (Brown *et al.* 2009), in reducing borrower-default rate (Jappelli & Pagano 2002), in reducing bank-lending corruption (Barth *et al.* 2009), in reducing bank risk (Houston *et al.* 2010) & banking crisis (Büyükkarabacak & Valev 2012), in increasing industrial growth (Houston *et al.* 2010) and in enhancing job growth (Ayyagari *et al.* 2016). We add to the literature by investigating the role of credit information sharing in reducing bank-specific stock price crash risk, which captures asymmetry in risk or the third moment of the stock return distribution. This role is distinct from the effect of credit information sharing on stock return performance (first moment) or firm risk (second moment) documented in prior studies. Thus, our findings broaden our understanding of the economic consequences of credit information sharing on banks and investors.

Second, we contribute to an empirical assessment of the effects of bank regulation and supervisions on bank development, performance and stability. Previous studies show that greater capital regulation stringency, greater supervisory power, and increased market-based monitoring promote bank efficiency. We further provide evidence that they serve as external governance mechanisms and can be viewed as substitutes for better information sharing schemes in reducing crash risk.

Last, our research contributes to the emerging literature that attempts to forecast future stock price crash risk (Jin & Myers 2006; Kim *et al.* 2011b; Kim *et al.* 2014). The literature on crash risk has captured much attention from both the investment community and academic researchers since the stock market collapse of 2001-2002 and 2008-2009. We complement prior studies on crash risk by examining a new factor that mitigates future stock price crash risk. Specifically, we discover that credit information sharing among banks about their borrowers is associated with lower crash risk. By examining crash risk, our study will be beneficial to firms, shareholders and investors who might want to manage tail risk in the stock market and incorporate crash risk in their portfolio and risk management decisions.

1.4 Structure of Thesis

The rest of the thesis proceeds as follows: Chapter 2 studies the impact of credit information sharing on the volume of bank lending. In addition, we test whether such impact varies with the transparency of the information environment and creditor rights. Chapter 3 investigates the impact of credit information sharing on bank risk. Furthermore, we test whether such impact varies with the transparency of the information environment and banking competition. Chapter 4 explores the impact of credit information sharing on bank-specific stock price crash risk. Moreover, we test whether such impact varies with the transparency of the information environment and banking regulation & supervision. Chapter 5 presents conclusion, limitation and a direction for future research.

Chapter 2: Credit Information Sharing and Bank Lending Decision: The Role of Information Asymmetry and Creditor Rights

2.1 Introduction

In credit markets, it is well known that information asymmetry leads to both adverse selection and moral hazard problems. Lenders are exposed to problems of information asymmetry, in which lenders are often not able to observe the characteristics of borrowers as well as their creditworthiness; thereby, cannot differentiate between safe and risky loan applicants. Besides the information about the borrowers' characteristics, lenders may also not be able to control the actions that borrowers could take after receiving loans and the problems of moral hazard could arise. As a result of both adverse selection and moral hazard, lenders may increase interest rate and/or this may result in market equilibrium with credit rationing and suboptimal allocation of capital (Stiglitz & Weiss 1981).

There are several ways banks can overcome these asymmetric information problems. Banks may engage in screening and monitoring of borrowers. For instance, they can interview loan applicants, visit their business before and after granting loans, and gather information from public records (Jappelli & Pagano 2002). If banks operate on a large scale, they can use these data for statistical risk management to grant and price loans based on past performance. Furthermore, collateral is commonly used as one of the tools to reduce asymmetric information (Bester 1985; Besanko & Thakor 1987). However, this requires that the borrowers have sufficient pledge-able assets or else they will not receive loans. Collateralization of loans is also often problematic especially for new firms, micro-entrepreneurs and small-medium enterprise, which often lack fixed assets to present as collaterals. Thus, the use of collaterals is not able to fully solve the problems resulting from asymmetric information. Another remedy for banks, however, is to share with other banks information on their borrowers. Formal information sharing takes place through privately held credit bureaus and publicly regulated credit registries. Such credit information sharing institutions disseminate knowledge of total debt exposure, payment history, and overall creditworthiness, thus bridging the information gap between banks and borrowers.

Theory shows that there are four mechanisms through which credit information sharing can alleviate the asymmetric information problem in lending. First, credit information sharing improves the knowledge of loan applicants' characteristics so that banks can differentiate between safe and risky borrowers, reducing the problem of adverse selection (Pagano & Jappelli 1993).Second, credit information sharing reduces the information monopoly a bank has on its borrowers so that borrowers are not held up (Sharpe 1990; Padilla & Pagano 1997). Third, the information sharing mechanism exerts a disciplinary effect on borrowers by encouraging them to perform and maintain a good reputation because the information about their defaults is shared among other banks (Klein 1992; Vercammen 1995; Padilla & Pagano 2000). Finally, credit information sharing among banks prevents over-borrowing which arises in the case of multiple bank lending (Bennardo *et al.* 2014).

Nonetheless, the theory makes no clear-cut predictions about the impact of information sharing on the volume of bank lending. On one hand, credit information sharing increases bank lending unambiguously if it reduces the information monopoly a bank has on its borrowers and induces borrowers to exert more effort to repay (Padilla & Pagano 1997) and if it prevents over-borrowing (Bennardo *et al.* 2014). On the other hand, credit information sharing may either increase or decrease the volume of bank lending with the composition of safe and risky borrowers (Pagano & Jappelli 1993) and the type of information being shared (Padilla & Pagano 2000). The question of how information sharing affects the volume of bank lending is, thus, left to the empirical study.

There are a few empirical studies on the impact of credit information sharing on bank lending (Jappelli & Pagano 2002; Djankov *et al.* 2007; Brown *et al.* 2009). Their findings examine the impact of credit information sharing on firms' access to credit (demand-side) and the volume of country-level aggregate lending. These studies agree that credit information sharing increases bank lending. Specifically, by analyzing the impact on firms' access to credit, Brown *et al.* (2009) shows that credit information sharing improves access to credit for firms in transition countries of Eastern Europe. By examining the country-level aggregate lending, both Jappelli and Pagano (2002) and Djankov *et al.* (2007) show the volume of private credit increases with credit information sharing.

However, the empirical evidence on the bank-level lending (supply side) evidence is still scarce. As the theory is ambiguous on the predicted impact of credit information sharing on bank lending, we attempt to fill in the gap by using a more recent data and providing a cross-country bank-level data analysis around the globe. Thus, our objective is to explore the impact of credit information sharing on bank lending. Although Fosu (2014) claims on his paper to be the first bank-level evidence of the effect of credit information sharing on bank lending, his finding is limited to African countries. It is not only meaningful to analyze the impact of credit information sharing schemes on credit market performance in African countries (Fosu 2014) or transition countries of Eastern Europe and the former Soviet Union (Brown *et al.* 2009) because information asymmetries are a pervasive problem affecting the performance of credit markets and credit information arrangements are one of the important institutions that significantly alleviate such problem and improve the credit allocation around the world (Djankov *et al.* 2007).

Moreover, rather than using country-level data on lending (Jappelli & Pagano 2002; Djankov *et al.* 2007), we study the impact of credit information sharing on bank lending by using bank-level panel dataset around the globe. Bank-level data ensures that individual banks' reactions to credit information sharing are not confounded by aggregate variation in credit allocation. In particular, bank-level data helps to isolate variations in credit allocation arising from (unobserved) heterogeneity of banks. In addition, because we utilize bank-level data, as opposed to firm-level data (Brown *et al.* 2009), we are able to study the determinant of bank lending volume from the banks' viewpoint, an approach consistent with theoretical analyses of information sharing in the credit market (Pagano & Jappelli 1993; Padilla & Pagano 1997, 2000; Bennardo *et al.* 2014).

Unlike existing studies, another objective is to investigate whether the effect of credit information sharing on the volume of bank lending depends on the transparency of the information environment and creditor rights in each country. To examine the impact of the information environment, we argue that the problem of asymmetric information between banks and borrowers is less problematic when the information environment is transparent. In more transparent information environment, borrowers are relatively less opaque and banks can easily acquire necessary information about potential loan applicants. In such information environment, the benefits of credit information sharing among banks should be relatively less effective in increasing bank lending. Our argument is also supported by Brown *et al.* (2009), who find that credit information sharing and firm-level transparency are substitutes in enhancing credit availability.

To examine the role of creditor rights, we rely on the study of Djankov *et al.* (2007) and Houston *et al.* (2010). Djankov *et al.* (2007) examine the association between credit information sharing, creditor rights, and private credit. However, our study is different from their study in two ways. First, we use a bank-level lending dataset to revisit such nexus. Second, we employ more comprehensive measures of credit information sharing from the World Bank's Doing Business. When banks are better protected, banks can more easily force repayment, grab collateral, or even gain control of the firm (Townsend 1979; Aghion & Bolton 1992; Hart & Moore 1994, 1998). As a result, they are more willing to grant loans, regardless of the riskiness of borrowers. Thus, the effect of credit information sharing on bank lending should be less pronounced in countries with strong creditor rights.

To test our predictions, we use a cross-country sample of 16,009 banks in 113 countries during the period of 2005 to 2013. After controlling for several bank-specific and country-specific factors, we find that credit information sharing is positively related to bank lending. This finding suggests that credit information sharing promotes bank lending. In other words, bank lending increases in countries where credit information sharing is intensely established.

In addition, we also find that the impact of credit information sharing on bank lending is less pronounced with more transparency of the information environment. Specifically, mandatory IFRS adoption and greater extent of business disclosure attenuate the effect of credit information sharing on bank lending. Moreover, we find that credit information sharing only affects bank lending through its interaction with credit rights. The results show that credit information sharing reduces bank lending in countries with strong creditors rights, while it has no notable effect on lending in countries with very poor creditor rights.

Our study in this chapter contributes to the literature in two ways. First, we contribute to the emerging literature on information sharing in credit markets. We examine how information sharing impacts the volume of bank lending an effect ambiguous in theory and underexplored empirically. Specifically, we provide empirical evidence on the supply side of bank lending, which is still scarce. Unlike country-level data, bank-level data ensures that individual banks' reactions to credit information sharing are not confounded by aggregate variation in credit allocation. In particular, bank-level data helps to isolate variations in credit allocation arising from (unobserved) heterogeneity of banks. In addition, because we utilize bank-level data, as opposed to firm-level data (Brown *et al.* 2009), we are able to study the determinant of bank lending volume from the banks' viewpoint, an approach consistent with theoretical analyses of information sharing in the credit market (Pagano & Jappelli 1993; Padilla & Pagano 1997, 2000; Bennardo *et al.* 2014).

Second, we use bank-level lending and more comprehensive measures of credit information sharing to revisit the cross-country association between credit information sharing, creditor rights, and bank lending. In general, previous cross-country studies (Jappelli & Pagano 2002; Djankov *et al.* 2007) only consider a dummy equals to one if any information sharing institution operates in the country, and zero otherwise. However, our study employs more comprehensive measures of credit information sharing from the World Bank's Doing Business, which considers the scope, coverage, and accessibility of credit information available through either a private credit bureau or a public credit registry. In addition, we provide alternative measures of credit information sharing with private credit bureau coverages (% of adult population) and public credit registry coverages (% of adult population) to measure the level of credit information sharing through each agency.

In summary, this chapter attempts to answer these following questions, which are graphically displayed in Figure 2-1 and Figure 2-2:

1. How, and to what extent, credit information sharing affects bank lending?
2. How, and to what extent, information asymmetry (as measured by IFRS adoption and BDI) and creditor rights affect the relationship between credit information sharing and bank lending?

The rest of the chapter proceeds as follows: Section 2 reviews the theoretical literature and provides empirical evidence as well as an outline of hypotheses development. Section 3 provides a description of data and methodology. Section 4 provides the empirical results and robustness tests are presented in Section 4. Section 5 presents the conclusion.

2.2 Literature Review and Hypotheses Development

2.2.1 Credit Information Sharing and Bank Lending

Theoretical Framework

In principle, exchanging information about borrowers can have four effects on credit markets. First, it reduces adverse selection faced by the lenders (Pagano & Jappelli 1993). Second, it reduces the hold-up problem stemmed from the lenders' ability to extract informational rents from borrowers within lending relationships (Sharpe 1990; Padilla & Pagano 1997; Von Thadden 2004). Third, it acts as borrower disciplinary device to reduce moral hazard problem making borrowers exert more effort to repay (Vercammen 1995; Padilla & Pagano 2000). Fourth, after revealing the overall indebtedness of borrowers, it reduces over-borrowing that is a result of the borrowers' ability to borrow a small amount from multiple lenders and become over-debted (Bennardo *et al.* 2009, 2014).

The first effect is that information sharing can reduce adverse selection in lending. Exchanging credit information provides banks with more knowledge of loan applicants' characteristics and allows more precise prediction of repayment rate. According to Pagano and Jappelli (1993), they show that credit information sharing reduces adverse selection in bank lending. In the pure adverse selection model developed by Pagano and Jappelli (1993), they show that information sharing improves the pool of borrowers, decreases defaults and reduces the average interest rate. If banks exchange their private information about their borrowers' quality, then they can correctly identify the applicants who are creditworthy and price their loans better. Since all banks do not have the same information about all borrowers, information sharing among banks can help make the right decision to safely lend to the new loan applicants who previously borrow from other banks. As a result of this, the defaults decrease. However, the effect of information sharing on the amount of lending is still ambiguous because the change in the volume of lending depends on the force between the increase in lending to safe borrowers and the decrease in lending to risky one. Total lending increases if the increase in lending to safe borrowers is more than the decrease in lending to risky one.

The second effect is that information sharing reduces a hold-up problem, which occurs from banks having private information about firms. When banks possess private information, this creates an informational advantage against other competitors and allows banks to extract higher interest rate from their customers in the future (Sharpe 1990; Von Thadden 2004). According to Padilla and Pagano (1997), they make this point in the context of a two-period model where each bank has private information about their borrowers. From this informational advantage, it gives banks some market power to extract the informational rent by charging higher interest rate in the future; thus, creating a hold-up problem. Knowing this, borrowers put low effort to perform to repay their debts. However, with the presence of credit information sharing, it restrains banks' bargaining power to extract information rents in the future. As a result, borrowers have greater incentive to invest effort in their project to ensure its success; thus, making borrowers more likely to repay, which in turn induces banks' willingness to lower lending rates and extend more credit. Thus, information sharing in this case unambiguously increases the volume of bank lending.

The third effect is that information sharing reduces moral hazard making borrowers become disciplined in their repayment. Klein (1992) shows that when the legal environment makes it difficult for banks to enforce credit contracts, information sharing can encourage borrowers to repay loans because they know that defaulters will be blacklisted. The disciplinary effect is also supported by Vercammen (1995). Padilla and Pagano (2000) also support this effect showing that sharing information about borrowers' past default creates a disciplinary effect instead of sharing borrowers' characteristics. Default information is a signal for bad quality for outside banks and a penalty like higher interest rate is needed. To avoid a penalty, borrowers exert more effort leading to lower default probability, lower interest rate, and higher banks' willingness-to-lending. Contrasting with the result of Padilla and Pagano (1997), sharing information about borrowers' characteristics in the model of Padilla and Pagano (2000) has no effect on default and interest rates. In addition, sharing borrowers' characteristics in the model of Padilla and Pagano (2000) can even reduce willingness to lend because banks lose informational rents, so they require a higher probability of repayment which is unchanged in the model. It does not change because of the unchanged level of effort and default rate.

Finally, the fourth effect is that information sharing helps to reduce over-borrowing in multiple-lending relationships (Bennardo *et al.* 2014). Borrowing from several banks induces opportunistic behavior among borrowers, causing them to over-borrow (Petersen & Rajan 1994; Bennardo *et al.* 2014). Borrowers have incentives to take so much credit and end up default. Fearing over the overall indebtedness of their borrowers, banks may response by rationing credit, deny credit, or increase an interest rate. Bennardo *et al.* (2014) show that sharing credit information allows lenders to assess total outstanding debts of borrowers from all lending sources, so they can lend safely and over-borrowing, as well as default, are less likely. Hence, in general, information sharing expands the availability of credit.

In summary, information sharing is considered to reduce default rate and interest rate but the effect on lending is still ambiguous across models. The predicted impact of information sharing on the volume of bank lending is ambiguous in the adverse selection model proposed by Pagano and Jappelli (1993), but the impact is positive in the hold-up model of Padilla and Pagano (1997) and in the multiple-bank lending model of Bennardo *et al.* (2009). Also, the types of sharing information determine the effect on lending volume as shown in the model of Padilla and Pagano (2000). Regarding to the model of Padilla and Pagano (2000), sharing only default data increases the volume of lending more than the level when banks also share borrowers' characteristics.

Empirical Evidence

On empirical front, most evidence supports that information sharing improves credit market performance. Country-level studies (Jappelli & Pagano 2002; Djankov *et al.* 2007) employ country-level aggregate data and confirm the positive effect of credit information sharing on bank lending to private sector. In addition, the study of Jappelli and Pagano (2002) find that the impact is similar regardless of the private or public nature of the information sharing mechanism. Public credit registers are less likely to be established in countries where private credit bureau already exists. Djankov *et al.* (2007) extend the study of Jappelli and Pagano (2002) by increasing the number of the country from 43 to 129 countries around the world. They also find that the ratio of private credit to GDP rises following either the improvement of creditor rights or the incidence of credit registries. The effect of information sharing is stronger in the poor countries.

Regarding firm-level evidence, Love and Mylenko (2003) use a cross-sectional firm-level data from the World Business Environment Survey (WBES) and find that private credit bureaus are associated with lower firm's financing constraints and a higher share of bank financing, while no significant effect of public credit registries on firm's financial constraints. This contrasts the result from Djankov *et al.* (2007) who find the significant impact of public credit registries on credit to private sector in poorer countries.

Extension of the work by Love and Mylenko (2003), Brown *et al.* (2009) employ both cross-sectional and panel estimations. They find that information sharing is related to improved credit availability and lower cost of credit to firms in 24 transition countries of Eastern Europe and the former Soviet Union. Using a cross-sectional analysis, they provide additional evidence that credit information sharing is beneficial to opaque firms more than transparent firms, and the impact is stronger in countries where legal environments are weak. This result suggests that information sharing and accounting transparency are substitutes in improving the availability of credit. By employing a panel data, they also find that information sharing improves access to credit and reduces the cost of finance in countries amid poor protection of creditors. However, information sharing has no effects on countries that creditors are well protected. This suggests that information sharing is a substitute for creditor rights, which is consistent with the result of Djankov et al. (2007).

Regarding bank-level evidence, Grajzl and Laptieva (2011) use bank-level panel data on Ukraine and find that information sharing through private credit bureau increases the volume of bank lending while there is no significant effect of information through the public credit registry on the volume of credit. This insignificant impact of the public credit registry on the volume of credit is inconsistent with the result found by Djankov *et al.* (2007), in which the impact of public credit registry is positively correlated with the volume of credit in poorer countries.

Covering African countries, Fosu (2014) explores the effect of credit information sharing on bank lending using bank-level data from African countries from 2004 to 2009. The results suggest that bank lending increases with credit information sharing. Furthermore, employing banking market concentration measures, he finds that the increase in bank lending decreases with banking market concentration suggesting that information asymmetry is less of a problem in more concentrated banking markets. Interpreting differently, banking concentration is less harmful when there is more asymmetric information (no credit information is shared).

As several of country-level, firm-level, and bank-level evidence support the positive impact of credit information sharing on the availability of credit, it is expected that credit information sharing to have a positive impact on bank lending. Therefore, we hypothesize as follows:

Hypothesis 1: Credit information sharing is expected to increase bank lending.

2.2.2 Credit Information Sharing, Information Asymmetry and Bank lending

A major challenge for any economy is to optimally allocate savings to new or existing investment opportunity. There are two main problems that prevent the efficient allocation of savings to potential business investment opportunity. They are "information problem" and "agency problem".

The information problem arises from the informational differences between firms and investors. Firms typically have more information about their expected earnings from current and future investment opportunity. This information asymmetry makes it difficult for investors to assess the real profitability of the firm's investment opportunity. The firms can even have an incentive to overstate their profitability that worsens the situation leading to market failure (Akerlof 1970). The result of information problem (so-called "lemons problem") gives firms an incentive to disclose additional information that could facilitate investors' decision (Akerlof 1970; Healy & Palepu 2001; Beyer *et al.* 2010).

The agency problem arises because investors do not engage in a direct control of a firm and the use of the funds once it flows to the firm and the self-interested entrepreneur has an incentive to expropriate investors' funds. If the investors invest in a form of equity of a firm, then the entrepreneur can make use of the funds by acquiring perquisites, paying excessive compensation, or making an investment decision that can be harmful to the interests of outside investors (Jensen & Meckling 1979). If the investors invest in a form of debt, then the entrepreneur can make use of the funds by investing in a highly risky project, issuing additional more senior claims or paying out received cash as a dividend (Smith &

Warner 1979). This moral hazard problem prevents direct transfers of information between market participants.

Consequently, the information environment will be shaped by both information and agency problem. They give a rise to a role of financial reporting and an incentive for corporate disclosure (Beyer *et al.* 2010). Accounting theory states that financial reporting is required by investors for evaluating the return on potential investment and for monitoring the use of funds once committed. In addition, financial reporting can reduce information asymmetry by disclosing timely and relevant information (Frankel & Li 2004). Without a good quality and transparency of financial report, it is not possible for market participants like investors and creditors to fully and completely understand a company's financial condition as well as risks involved and a real fundamental of the company. Moreover, transparency of financial statement is crucial for corporate governance as it allows boards of directors to measure the effectiveness of management and detect any serious financial condition in order to take early corrective actions.

Therefore, both transparent accounting information and corporate disclosure with high quality and credibility would provide useful insight information for decision making by shareholders, stakeholders and potential investors in relation to capital allocation, corporate transactions and financial performance monitoring (Leuz & Wysocki 2008; Beyer *et al.* 2010). However, generally, firms do not always disclosure all information and voluntarily disclosure partial information. Firms voluntarily disclosure their private information under conditions identified by the unraveling result[1] (Grossman & Hart 1980; Grossman 1981; Milgrom 1981; Milgrom & Roberts 1986). If the unraveling result holds, a firm will provide all information voluntarily; however, in practice, the unraveling result has not been successful in explaining observed disclosure and this leads to less than full disclosure (Beyer *et al.* 2010).

[1] The conditions under the unraveling result are: (1) disclosure are costless; (2) investors know that firms have, in fact, private information; (3) all investors interpret the firms' disclosure in the same way and firms know investors will interpret that disclosure; (4) managers want to maximize their firms' share prices; (5) firms can credibly disclosure their private information; and (6) firms cannot commit ex-ante to a specific disclosure policy.

Despite the incentives of voluntary disclosure, Leuz and Wysocki (2008) explain the reasons why disclosure regulation is needed. First, sometimes it is difficult for managers to credibly convey information due to misalignment of insiders' and investors' incentives. Thus, disclosure requirement and accounting standards play a crucial role in allowing firms to commit to a certain level of disclosure and, at the same time, improve the credibility of reporting information. Second, because disclosures are considered as public goods, this causes a lack of incentive to voluntarily disclosure certain information, which can improve social welfare. Disclosure regulation thus comes into play when firms do not voluntarily disclose all private information.

Therefore, we focus on the mandatory adoption of International Financial Reporting Standards (IFRS) to measure the transparency of the macro information environment. IFRS is developed by the International Accounting Standards Board (IASB), which operates under the oversight of the IFRS Foundation. The goal of the IASB and the IFRS Foundation is to develop a single set of global financial reporting standards that bring transparency, accountability, and efficiency to financial markets around the world. Those standards serve the public interest by fostering trust, growth, and long-term financial stability in the global economy.

Studies show that IFRS adoption may improve analysts' information environment by enhancing transparency and by increasing the comparability of the financial reports (e.g. Barth *et al.* (2008b); Bae *et al.* (2008)). Cross-border comparison of financial data becomes easy when the single set of accounting standard is applied globally; thereby, decreasing information acquisition costs, increasing competition and efficiency in the markets (Ball 2006).

Existing research studies on mandatory IFRS adoption initially examine the pre-impact of mandatory IFRS adoption (Comprix *et al.* 2003; Armstrong *et al.* 2006; Christensen *et al.* 2007a). These studies find a positive market reaction to events that increase the likelihood of IFRS adoption, though the effect might be small in some countries (e.g. UK). Several other studies, on the other hand, observed the outcome of the capital market after the introduction of mandatory IFRS adoption. Some studies show that stock market liquidity and equity valuations increase after the introduction of mandatory IFRS in a country (Platikanova 2007; Daske *et al.* 2008). Moreover, IFRS reconciliations contain new information that investors consider relevant for firm valuation (Christensen *et al.* 2007b). Most accounting quality indicators have improved after mandatory adoption of IFRS (Jeanjean & Stolowy 2008; Chen *et al.* 2010). The mandatory IFRS adoption also increases both private and public information to analysts resulting in the improvement of analysts' information environment (Ashbaugh & Pincus 2001; Byard *et al.* 2011; Horton *et al.* 2013).

Consistently, empirical analysis on voluntary IFRS adoption is found to result in better transparency of financial reporting, higher accounting quality and lower information asymmetry, uncertainties and estimation risks (Leuz & Verrecchia 2000; Daske & Gebhardt 2006; Hung & Subramanyam 2007; Barth *et al.* 2008b), lower bid-ask spreads (Leuz & Verrecchia 2000), increased analyst following (Cuijpers & Buijink 2005), lower cost of capital (Daske *et al.* 2013) and higher foreign institutional investment (Covrig *et al.* 2007).

The key challenge for the study of voluntary IFRS adoption is the fact that firms choose whether and when to adopt IFRS reporting. It is difficult to differentiate between mandatory and voluntary IFRS when the adoption of IFRS is voluntary for certain sectors in the economy. A country may allow some firms to conform to IFRS; however, local GAAP[2] is still allowed for others such that it is impossible to observe the effects of IFRS adoption per se. Thus, we prefer using mandatory IFRS adoption as a proxy for asymmetric information environment. When a country mandatorily adopts IFRS, the macro information environment is more transparent compared to a country with no IFRS adoption.

In addition to mandatory IFRS adoption, we employ an alternative measure of the transparency of information environment, which is the Business Extent of Disclosure Index (BDI). BDI is obtained from the World Bank's Doing Business. This index measures the extent to which investors are protected through disclosure of ownership and financial information (World Bank's Doing Business 2016). Particularly, BDI is a measure of the extent of disclosure of a firm's conflict of interest. The index measures how well are minority shareholders protected from disclosure of transactions that involve conflicts of interests. Misbehavior or misuse of funds by entrepreneurs can eventually be harmful to the interests of shareholders and fund providers (Jensen & Meckling 1979). Greater business disclosure

[2] Local GAAP standards for Generally Accepted Accounting Practices.

would make firms more discipline and reduce the moral hazard problem. Thus, higher BDI is associated with higher level of transparency of information environment.

Information asymmetry is the main explanation for credit rationing, suboptimal allocation of capital and inefficient investment decisions leading to an adverse economic outcome (Stiglitz & Weiss 1981; Myers & Majluf 1984; Diamond & Verrecchia 1991). Theoretical and empirical studies show that credit information sharing can mitigate information problems between banks and borrowers, leading to safe and credit availability. However, the usefulness of credit information sharing in reducing information gaps between banks and borrowers can be less effective in a country with more transparent information environment compared to one with lower transparent information environment.

To the best of my knowledge, no empirical study attempts to study the impact of information asymmetry on the relationship between credit information sharing and bank lending. There is one study seeking to estimate the impact of information sharing on access to finance for firms. Specifically, Brown *et al.* (2009) suggest that firm-level accounting transparency is a substitute for credit information sharing in enhancing firms' access to credit; the correlation between credit information sharing and credit access is stronger for opaque firms than for transparent ones. However, their study is related to firm-level survey data on access-to-finance but not the supply side of bank lending, which is an approach consistent with theoretical analyses of information sharing in the credit market (Pagano & Jappelli 1993; Padilla & Pagano 1997, 2000; Bennardo *et al.* 2014).

Since the study on the impact of information asymmetry on the relationship between credit information sharing and bank lending is scared, we examine such impact by employing the mandatory adoption of IFRS and BDI as proxies for the macro information environment. Based on the support from the empirical evidence that the adoption of IFRS enhances transparency and information environment, we expect that the beneficial effect of credit information sharing on bank lending is reduced in countries with mandatory IFRS adoption. For an alternative proxy of information environment to IFRS adoption, we also expect that higher BDI would attenuate the impact of credit information sharing on bank lending. Formally, we hypothesize that:

Hypothesis 2: The impact of credit information sharing on bank lending is expected to be less pronounced when the information environment is more transparent (as proxied by IFRS adoption and BDI).

2.2.3 Credit Information Sharing, Creditor Rights and Bank Lending

Several papers have examined the effects of stronger creditor rights in bankruptcy of non-financial firms. John *et al.* (2008) find that stronger corporate governance is correlated with greater corporate risk-taking. At the same time, Acharya *et al.* (2011) find that stronger creditor rights lead to reduced corporate risk-taking in the form of diversifying acquisitions. Claessens and Klapper (2005) find that the various components of the popular creditor rights indexes have a differential effect on the likelihood of bankruptcy, while Brockman and Unlu (2009) find that companies are less likely to pay dividends in countries with weaker creditor rights.

Recent papers investigate the role of creditor rights and credit information sharing and their interaction. The importance of creditor power and credit information sharing on the credit availability have been empirically studied by Djankov *et al.* (2007), and they find that both stronger creditor rights and the existence of information sharing institution are associated with the higher ratio of private credit (% of GDP). Their measure of information sharing used by Djankov *et al.* (2007) is based on a dummy, whose value is equal to one if any information-sharing institution exists in the country and zero otherwise.

The impact of creditor rights and information sharing on bank's behavior is also examined by Houston *et al.* (2010). They suggest that there is both a bright side and dark side from enhancing creditor protections. On the bright side, stronger creditor rights appear to encourage banks to take on more risks which helps provide valuable capital to private firms which enhances overall economic growth. On the downside, the dark side of greater risk-taking is that it significantly increases the likelihood of financial crisis. Unlike the conflicting effects of creditor rights protections, they argue that information sharing among creditors appears to be universally beneficial. Specifically, information sharing reduces information symmetries and enhances transparency, which reduces bank risk-taking and the likelihood of a crisis, while at the same time promoting economic growth.

The effects of creditor rights and information sharing on bank's behavior are likely to be even more complex than considering one by one. Creditor rights and information sharing not only affect borrower's incentives for risk-taking, which influence the risk of any specific loan, but they also may influence a bank's willingness to lend to riskier borrowers, the bank's mix of securities and loans, and the bank's willingness to hold capital—all of which have important effects on the bank's overall level of risk.

According to Houston *et al.* (2010), for a given set of borrowers, we might expect that, all else equal, stronger creditor rights would translate into lower bank risk-taking because lenders are more likely to grab collateral, force repayment, or even gain control of the debtor that is in financial distress resulting in higher recovery rate or lower risk in the event of borrower's default. In addition, borrowers are also less willing to take risks when they know that creditors are well protected. However, stronger creditor rights may encourage banks to provide loans to a wider (potentially riskier) set of borrowers and result in increased expected default rate in the bank's portfolio. In their empirical study, they find that stronger creditor rights are correlated with higher bank risk-taking. Furthermore, they also find that information sharing among creditors reduces bank risk-taking and mitigates the effect of creditor rights on bank risk taking.

Absent in the paper of Houston *et al.* (2010) is the influence of creditor rights and credit information sharing on the level of bank lending. There is potentially an interactive effect between creditor rights and credit information sharing on bank lending. One possibility is that the strong creditor rights grant more power to creditors when borrowers go bankrupt, making them more willing to extend credit to potentially riskier borrowers. Another possibility is the role of credit information sharing among creditors in reducing the costly information asymmetries, which also allow lenders to provide more loans. Based on two possibilities, we argue that information sharing might be less beneficial in increasing lending if creditors are well protected. Because banks know that they are well protected, so they are willing to lend to a broader and riskier set of borrowers while ignoring whether borrowers are a safe or risky type.

Thus, if we consider creditor rights and information sharing per se, then we would see a positive individual impact on lending. However, if we consider their interaction, then we could see that the impact of credit information on bank lending maybe less pronounced with strong creditor rights. Formally, we hypothesize as follows:

Hypothesis 3: The impact of credit information sharing on bank lending is expected to be less pronounced when the protection of creditor through the legal system is strong.

2.3 Data and Methodology

2.3.1 Data

2.3.1.1 Data Sources and Sample

The sample in this chapter consists of 16,009 banks in 113 countries during the period 2005 – 2013. We only use data in the year 2005 to construct all explanatory and control variables for predicting the dependent variable in the year 2006. We compile data from several different sources. The main database used in this chapter is the *Bankscope Database* to obtain bank-level accounting information.

For explanatory variables, we rely on the *World Bank's Doing Business Database* to obtain cross-country data on credit information sharing and the business extent of disclosure index (BDI). Data on IFRS adoption is obtained from three different sources which include the *IFRS Foundation website*, *Deloitte* and *Simon Fraser University in Canada*[3]. Data on the level of creditors' protection through the legal system is extracted from the Dataset from *LaPorta et al. (1998) and Djankov et al. (2007)*[4].

Other variables are taken from the *World Bank's World Development Indicators (WDI) Database*, the *World Bank's World Governance Indicators (WGI)*, the *World Bank's Bank Regulation & Supervision Survey Database,* the *Deposit Insurance Database*, the *Central Intelligence Agency (CIA)* and the dataset from *Easterly (2001)* and *La Porta et al. (1999)*. Further descriptions and links to data sources can be found in Appendix A.

2.3.1.1 Variable Measurements

2.3.1.1.1 Dependent Variable

For the bank-lending variable, we extract total gross loans from the BankScope database. A total gross loan of each bank is defined as total amount of loans to household

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[3] We cross-check the data within these three sources to ensure that the country mandatorily adopt IFRS and the effective date of the mandatory IFRS adoption is correct.

[4] La Porta et al. (1998) provide data on the creditor rights index to measure the power of creditors in the vent of borrowers' bankruptcy. Djankov et al. (2007) extend the dataset of LaPorta et al. (1998) on creditor rights index to include as many as 129 countries.

and firms. The unit is expressed in term of million US dollars. In addition, we take a natural logarithm of total gross loans and take the difference between the natural logarithm of gross loans in the current period and the natural logarithm of gross loans in the previous period. Mathematically,

$$GLOAN_{i,t} = log\left[LOAN_{i,t}\right] - log\left[LOAN_{i,t-1}\right] \tag{2-1}$$

Where log is a natural log function; $LOAN_{i,t}$ is total gross loans of bank i[th] at time t and $LOAN_{i,t-1}$ is total gross loans of bank i[th] at time t-1. We can interpret the changes in natural logarithms as percentage changes after multiplying by 100. We define the changes in the natural logarithms of gross loans as *GLOAN*.

2.3.1.1.2 Explanatory Variables

Credit Information Sharing Proxy

The key independent variable in our analysis the variable measuring the level of credit information sharing across countries. Generally, banks exchange information about their borrowers' creditworthiness through information-sharing institutions. These information-sharing institutions exist as either privately held credit bureaus or publicly regulated credit registries. According to Djankov *et al.* (2007), a private credit bureau is a database maintained by a private commercial firm whereas a public credit registry is a database maintained by a public authority (e.g. central banks). Both information-sharing institutions consolidate information on the borrowers' creditworthiness in the financial system and facilitate the exchange of credit information among banks and other financial institutions. However, the contents and scope of credit information available from credit information institutions may vary across countries. Some institutions may collect information on outstanding loans of large borrowers, while some others may provide extensive information consisting of demographic data, default records, late payment (delinquency), credit inquiries, ratings, payment of utility bills (Miller 2003; Djankov *et al.* 2007).

We thus use the depth of credit information sharing index (*DEPTH*) to capture the differences of information contents across countries. The index is taken from the World Bank's Doing Business database. This index measures rules affecting the scope, accessibility, and quality of credit information available through either private credit bureau or public credit registry (Djankov *et al.* 2007; Houston *et al.* 2010). The depth of credit information sharing index ranges from zero to six with higher values indicating better scope, accessibility, and quality of credit information available from either private credit bureau or public credit registry. The value of zero indicates that there is no private credit bureau or public credit registry operating in a country. The value of one is then added to the index with each one of the following characteristics:

- Both positive information and negative information are distributed. Positive information is an information about loans outstanding and pattern of on-time repayments, whereas negative information is an information about late payments, number and amount of defaults, arrears or bankruptcies.
- Data on individuals (households) and firms are distributed.
- Data from retailers, trade creditors, and/or utility companies as well as financial institutions are distributed.
- More than 2 years of historical data are available. Registries that erase data on defaults as soon as they are repaid would receive a score of 0 for this indicator.
- Data are collected and distributed on loans with value below 1% of income per capita. A registry must have a minimum coverage of 1 percent of the adult population to score a 1 for this indicator.
- Laws give right to borrowers to inspect their own data.

Information Environment Proxy

To measure the transparency of the information environment, we rely on two proxies which are the mandatory IFRS adoption and the Business Extent of Disclosure Index (BDI). Regarding mandatory IFRS adoption, we identify each country’s status of IFRS adoption and build a dummy variable whose value is equal to 1 for a country (and year) that mandatorily adopts IFRS and 0 otherwise. We name this dummy IFRS. For a country’s date of IFRS adoption, we refer to the effective date of IFRS implementation. We define countries with mandatory IFRS adoption to be more transparent than those without. IFRS dummy with a value of one is associated with more transparent information environment. The list of countries with mandatory IFRS adoption is in Appendix B.

Regarding BDI, the data is obtained from the World Bank's Doing Business. This index measures the extent to which investors are protected through disclosure of ownership and financial information (World Bank's Doing Business 2016). It ranges from 0 to 10 with a higher value indicating more disclosure of ownership and financial information to investors. Thus, a higher (lower) BDI indicates that the information environment is more (less) transparent. More detail of the components of BDI is in Appendix C.

Creditor Rights Index

The measure of creditor powers in the event of borrowers' bankruptcy is an aggregate measure of creditor legal protection created based on the methodology proposed by LaPorta *et al.* (1998). The index is ranging from zero to four. The index consists of 4 components:

- Restrictions on reorganization: whether there are restrictions imposed, such as creditors' consent or minimum dividend, when a debtor files for reorganization.
- No automatic stay: whether secured creditors can gain possession of assets after the petition for reorganization is approved, that is, whether there is no automatic stay or asset freeze imposed by the court on a creditor's ability to seize collateral.
- Secured creditor paid first: whether secured creditors are ranked first in the distribution of proceeds of liquidating a bankrupt firm as opposed to other creditors such as government or workers.
- No management stay: whether the incumbent management does not stay in control of the firm during the reorganization, in other words, whether an administrator, not the management, is responsible for running the business during the reorganization.

A value of one is added to the index when a country's laws and regulations provide each of these powers to secured lenders. A higher index indicates that secured lenders are better protected in case a borrower defaults.

2.3.1.1.3 Control Variables

We include a series of control variables to prevent the spurious relationship between credit information sharing and bank lending or avoid any relationship that could be driven by unobserved variables. To control for bank characteristics, we include bank's size, profit margin, and efficiency. The size of each individual bank is empirically proxied by a natural logarithm of bank's total assets (*SIZE*). We measure the profitability of each bank with a bank's net interest revenue as a share of its interest-bearing assets. This variable is a net interest margin (*NIM*). This variable measures the profitability of investing and lending activities. To control for the bank's efficiency in operating on and off-balance sheet activities, we incorporate a ratio of total expenses to operating income (interest and non-interest income). This ratio is simply a cost-to-income ratio (*EFFICIENCY*). Beside bank's size, profitability, and efficiency, we also include a ratio of total deposits to total assets (*DEP*) and a ratio of loan loss reserves to gross loans (*LLR*).

To control for country-specific macroeconomic performance, we include a growth rate of gross domestic product (*GDPG*) and an inflation rate (*INF*). All are collected from WDI. The growth rate of GDP is included to capture the development of the economy (Djankov *et al.* 2007). Inflation is proxied by a consumer price index (CPI) to control for the price movement and uncertainty in the credit market. Uncertainty in the credit market arises from the banks' difficulty in assessing the quality of credit because profits in real term become harder to predict during periods of high inflation. We also control for the banking market structure by including the ratio of three largest bank's assets in a country to the total assets in the banking system (*CCT3*). Lastly, we include a capital stringency index (*CAPITAL_STR*), measuring the extent of both initial and overall capital stringency in a country.

2.3.1.1.4 Summary Statistics

Table 2-1 summarizes all definitions and sources of variables as well as their symbols used in this chapter. Descriptive statistics for the main empirical results and robustness checks are displayed in Table 2-2. All variables are winsorized at the 1% and 99% levels. The sample consists of 16,009 banks in 113 countries over the period of 2005 to 2013. From the table, on average, the change of the natural logarithm of total gross loans (*GLOAN*) has a mean about 0.089 (or 8.9%). The depth of credit information sharing index (*DEPTH*) has mean (median) of 5.01 (5), indicating that most observations in the sample have a high scope, accessibility, and quality of credit information available through credit information sharing agencies. For other alternative measures of credit information sharing, the private credit bureau coverage (*PRIV*) is about 79%, while the public credit registries coverage (*PUB*) is about 9.8%. Regarding the proxies of information asymmetry, the table shows that the mean of IFRS adoption (*IFRS)* is 0.305, meaning that more than half of observations have no IFRS adoption, while the mean of the business extent of disclosure index (*BDI*) is 6.42. The mean of creditor rights index (*CR*) is 1.54, showing that on average the degree of creditor protection is not high around the globe.

The summary statistics of main control variables are also shown in the same table. According to the bank characteristics controls, the mean of the natural logarithm of bank's assets (*SIZE*) is around 6; the mean of the net interest margin (*NIM*) is around 4%; the mean of the cost-to-income ratio (*EFFICIENCY*) is around 71.6%; the mean of the deposit to asset ratio (*DEP*) is around 78.3%; and the mean of loan loss reserves to gross loans ratio (*LLR*) is 2.5%. For the macroeconomic controls, on average, the growth rate of gross domestic product (*GDP*) is around 2%, while the inflation rate (*INF*) is approximately 3.1 percent. Regarding the banking market structure, the banking market concentration ratio (*CCT3*) is on average 42.8%. Lastly, on average, the degree of overall banking capital stringency (*CAPITAL_STR*) is around 6 to 7.

In addition to the variables used in the main regression, we also present the summary statistics of the variables used as additional controls in robustness tests. The dummy of deposit insurance (*DEPOSIT_INS*) has a mean of 0.961 and a median of 1, implying that most of the observations in the sample have a deposit insurance regime. The effect of deposit insurance regimes might be absent due to the cluster of values around 1. Another additional control variable is the political stability index (*POLITIC*). The mean of *POLITIC* is 0.397 on the scale of +/-2.5.

Table 2-3 and Table 2-4 reports the correlation between variables. The table shows that *DEPTH* is positively correlated with *GLOAN,* indicating that there exists a positive relationship between credit information sharing and bank lending. Regarding alternative proxies of credit information sharing, *PRIV* is positively associated with *GLOAN* and highly correlated with *DEPTH*. This highly positive correlation between *PRIV* and *DEPTH* suggests that a country with the high depth of credit information tends to have high coverage of private credit bureaus or vice versa. However, each variable enters the regression individually, so the problem of multicollinearity should be less of a concern. Another proxy of credit information sharing, *PUB*, is, in contrast, negatively associated with *GLOAN* and negatively correlated with *DEPTH*. The two proxies of information asymmetry, *IFRS* and *BDI*, are positively correlated with *GLOAN*, suggesting that mandatory IFRS adoption and higher extent of disclosure index tend to promote lending and vice versa. The creditor rights index, *CR*, is also positively correlated with *GLOAN*. Notably, *DEPTH* is negatively correlated with each of proxy of information asymmetry (*IFRS* and *BDI*) and creditor rights index (*CR*), implying that their relationships are going in the opposite direction. However, their interaction effects on *GLOAN* will be examined further with multivariable regression analysis. The methodology will be explained in the next section.

2.3.2 Methodology

According to our hypothesis H1, we expect that credit information sharing has a positive impact on bank lending. The regression equation is as follows:

$$LENDING_{i,t} = \beta_0 + \beta_1 CIS_{i,t-1} + \sum_{k=2}^{5} \beta_k (X_{i,t-1}^{k}) + \sum_{m=6}^{9} \beta_m (Y_{i,t-1}^{m}) + \lambda_t + \alpha_i + \varepsilon_{i,t} \quad (2\text{-}2)$$

Where i, t and t-1 indicates the i[th] bank, year t and year t-1, respectively; $LENDING$ is bank lending measured by the change in the natural logarithm of total gross loans (*GLOAN*); *CIS* is a credit information sharing variable proxied by the depth of credit information sharing index (*DEPTH*); *X* contains bank-specific variables, consisting of bank's size (*SIZE*), net interest margin (*NIM*), a cost-to-income ratio (*EFFICIENCY*), a deposits to assets ratio (*DEP*), a loan-loss reserves to gross loans ratio (*LLR*); *Y* contains country-specific variables, consisting of GDP growth (*GDPG*), inflation (*INF),* banking concentration (*CCT3*) and capital stringency index (*CAPITAL_STR*); λ_t is the year fixed effects; α_i is the individual effects or the time-invariant component of the error term; and ε is an idiosyncratic error term or time-varying component of the error term. The coefficient β_1 reflects the impact of credit information sharing on bank lending. Thus, according to the hypothesis H1, we expect the sign of β_1 to be positive so that credit information sharing increases the volume of bank lending.

The year fixed effects. λ_t, are a set of time dummies included to control for economy-wide events and technological innovation affecting all banks equally across countries, which vary over time. These year fixed effects capture, for example, the economy-wide institutional changes affecting the quality of rules and laws governing the country, fluctuation in the market interest rate shaping the supply and demand of credit, conditions in the public debt market, which also influence bank lending decision. The year fixed effects can also include exogenous macroeconomic shocks, such as the spread of the global financial crisis in 2008 and 2009. The individual (or bank) fixed effects, α_i, captures the time-invariant heterogeneity of banks. For instance, the bank-level heterogeneity is due to initial differences in the managerial practices, the age of establishment, etc. all of which could be potential confounding factors in estimating the effect of credit information sharing on bank lending.

According to the hypothesis H2, we expect the effect of credit information sharing on bank lending to be less pronounced in a more transparent information environment as proxied by IFRS adoption or BDI. To test this hypothesis, we augment Equation (2-2) with one of the two proxies of the information environment and their interactions with the credit information sharing measure. The new regression model thus expresses as follows:

$$\begin{aligned} LENDING_{i,t} &= \beta_0 + \beta_1 CIS_{i,t-1} + \beta_2 ASYM_{i,t-1} + \beta_3 ASYM_{i,t-1} * CIS_{i,t-1} \\ &\quad + \sum_{k=4}^{7} \beta_k (X_{i,t-1}^k) + \sum_{m=8}^{11} \beta_m (Y_{i,t-1}^m) + \lambda_t + \alpha_i + \varepsilon_{i,t} \end{aligned} \tag{2-3}$$

Where i, t and t-1 indicates the i[th] bank, year t and year t-1, respectively; $LENDING$ is bank lending measured by the change in the natural logarithm of total gross loans (*GLOAN*); *CIS* is a credit information sharing variable proxied by the depth of credit information sharing index (*DEPTH*); *ASYM* represents one of the two proxies of information environment, namely IFRS adoption ($IFRS$) and the business extent of disclosure index (BDI); X contains bank-specific variables, consisting of bank's size (*SIZE*), net interest margin (*NIM*), a cost-to-income ratio (*EFFICIENCY*), a deposits to assets ratio (*DEP*), a loan-loss reserves to gross loans ratio (*LLR*); *Y* contains country-specific variables, consisting of GDP growth (*GDPG*), inflation (*INF),* banking concentration (*CCT3*) and capital stringency index (*CAPITAL_STR*); λ_t is the year fixed effects; α_i is the individual effects or the time-invariant component of the error term; and ε is an idiosyncratic error term or time-varying component of the error term. The coefficient β_3 reflects the extent to which degree of information environment moderates the impact of credit information sharing on bank lending; thereby, according to the hypothesis H2, we expect the sign of β_3 to be negative such that the impact of credit information sharing on bank lending is less pronounced with a more transparent information environment.

According to the hypothesis H3, we expect that the impact of credit information sharing on bank lending is less pronounced under the environment with better creditor protection. To test for the hypothesis H3, we augment Equation (2-2) with an index measuring the level of creditor protection and its interaction with the credit information sharing measure. The new regression model is thus as follows:

$$\begin{aligned} LENDING_{i,t} = {} & \beta_0 + \beta_1 CIS_{i,t-1} + \beta_2 CR_{i,t-1} + \beta_3 CR_{i,t-1} * CIS_{i,t-1} \\ & + \sum_{k=4}^{7} \beta_k (kX_{i,t-1}^{k}) + \sum_{m=8}^{11} \beta_m (Y_{i,t-1}^{m}) + \lambda_t + \alpha_i + \varepsilon_{i,t} \end{aligned} \tag{2-4}$$

Where i, t and t-1 indicates the i[th] bank, year t and year t-1, respectively; $LENDING$ is bank lending measured by the change in the natural logarithm of total gross loans (*GLOAN*); *CIS* is a credit information sharing variable proxied by the depth of credit information sharing index (*DEPTH*); *CR* is creditor rights index measuring the level of creditor protection through the legal system; *X* contains bank-specific variables, consisting of bank's size (*SIZE*), net interest margin (*NIM*), a cost-to-income ratio (*EFFICIENCY*), a deposits to assets ratio (*DEP*), a loan-loss reserves to gross loans ratio (*LLR*); *Y* contains country-specific variables, consisting of GDP growth (*GDPG*), inflation (*INF),* banking concentration (*CCT3*) and capital stringency index (*CAPITAL_STR*); λ_t is the year fixed effects; α_i is the individual effects or the time-invariant component of the error term; and ε is an idiosyncratic error term or time-varying component of the error term. The coefficient β_3 reflects the extent to which degree of creditor rights affects the relationship between credit information sharing and bank lending; thereby, according to the hypothesis H3, we expect the sign of β_3 to be negative so that the impact of credit information sharing on bank lending is less pronounced with better creditor protection.

In the robustness test, we re-estimate Equation (2-2) to Equation (2-4) with a few modifications and augmentations. We employ alternative measures of credit information sharing in each by replacing *DEPTH* with private credit bureau coverages (*PRIV*) and public credit registries coverages (*PUB*). Also, we add more country-level control variables that could potentially affect the volume of bank lending, including a deposit insurance dummy (*DEPOSIT_INS*) and political stability (*POLITIC*). In addition, we provide an instrumental variable regression by employing a legal origin dummy (*LEGALORIGIN*), ethnic fractionalization (*ETHNIC_FRAC*) and latitude (*LATITUDE*) as instrumental variables for credit information sharing and bank lending.

2.4 Empirical Results and Robustness Tests

2.4.1 Empirical Results

2.4.1.1 The Impact of Credit Information Sharing on Bank Lending

Table 2-5 shows model selection and diagnostic tests for the regression analysis. All tests are applied to Equation (2-2) with no interaction terms. Next, we select the estimation technique based on the tests and apply it to Equation (2-3) and Equation (2-4)[5]. The tests show that the fixed effect regression is preferable to the pool regression and the random effect regression. Moreover, it suggests that the problems of heteroscedasticity and serial correlation exist, so we adjust standard errors that are robust to heteroscedasticity and cluster standard errors at bank-level to account for within-cluster correlation of the error term[6].

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[5] Adding interaction terms would not significantly change the overall results of the tests much.
[6] More detail of model selection tests and diagnostic tests can be found in the Appendix F.

Table 2-6 presents the regression results for Equation (2-2). In all regression results on the table, the growth rate of the logarithm of total gross loans (*GLOAN*) is used as a dependent variable and the level of credit information sharing is proxied by the depth of credit information sharing index (*DEPTH*). T-statistics are reported in parentheses. The column 1 of the table reports the regression result for Equation (2-2). The coefficient of *DEPTH* (or β_1 in Equation (2-2)) is positive and significant (at 10% level), indicating that *GLOAN* is positively associated with *DEPTH*. The result is consistent with the hypothesis H1, suggesting that bank lending increases with more credit information sharing.

By assessing the marginal impact of credit information sharing on bank lending holding all other variables at their sample mean, we find that a one-unit increase of *DEPTH* increases gross loans by approximately 2.3%. Total gross loans can increase up to 13.8%, should the depth of credit information sharing index increases to six (switching from a regime without credit information sharing to a regime with fully-fledged credit information sharing). Our result reflects the notion that banks are willing to extend more credit in countries with more credit information sharing because the information problems between banks and borrowers are less severe. In particular, information sharing among banks alleviates the problems of adverse selection, moral hazard, hold-up problem and over-indebtedness that bank may face when they decide to extend credit (Pagano & Jappelli 1993; Padilla & Pagano 1997, 2000; Bennardo *et al.* 2014). As a result of a reduction in information problems, banks can price and lend to potential borrowers safely so that they are willing to grant loans.

Our finding is consistent with several studies attempting to study the impact of credit information sharing on firms' access-to-credit (Love & Mylenko 2003; Brown *et al.* 2009) and country-level private credit (Jappelli & Pagano 2002; Djankov *et al.* 2007). Those studies show that credit information sharing increases borrowers' access to credit and the level of aggregate private credit. Our finding complements their studies by providing evidence that credit information sharing also increases the supply of individual bank lending. The increase in bank lending with more credit information sharing is also in line with the study of Fosu (2014), who provides the impact of credit information sharing on bank lending in African countries. However, our result suggests that the benefit of credit information sharing on increasing bank lending is not limited to African countries but every country around the globe.

As opposed to country-level data, examining bank lending with bank-level data ensures that individual banks' reactions to credit information sharing are not confounded by aggregate variation in credit allocation. In particular, bank-level data helps to isolate variations in credit allocation arising from (unobserved) heterogeneity of banks. In addition, because we utilize bank-level data, as opposed to firm-level data (Brown *et al.* 2009), we are able to study the determinant of bank lending volume from the banks' viewpoint, an approach consistent with theoretical analyses of information sharing in the credit market (Pagano & Jappelli 1993; Padilla & Pagano 1997, 2000; Bennardo *et al.* 2014).

Regarding the bank-specific variables, we find that the bigger the size of the banks, as a proxy by total assets (*SIZE*), the larger the loans each bank offers. In addition, there is a significant positive correlation between net interest margin (*NIM*) and bank lending meaning that profitable banks lend more than less profitable banks. Less efficient banks, as reflected by a higher cost-to-income ratio (*EFFICIENCY*), tend to lend less compared to more efficient banks. Moreover, banks with lower a ratio of loan loss reserves to gross loans (*LLR*) lends more. Regarding the macroeconomic control variables, a higher rate of real GDP growth (*GDPG*) is positively associated with bank lending; however, we don't find that inflation (*INF*) affect bank lending decision. We also find that banking concentration (*CCT3*) and bank lending has no significant relationship. Last but not least, our results provide evidence that stringent capital regulation (*CAPITAL_STR*) is associated with lower bank lending.

2.4.1.2 The Impact of Information Asymmetry on the Relationship between Credit Information Sharing and Bank Lending

We have shown that credit information sharing increases bank lending; however, the impact can vary under different degree of the asymmetric information environment. Specifically, we test whether, and to what extent, the transparency of information environment affect the relationship between credit information sharing and bank lending. Information problems between banks and borrowers should be less problematic when the information environment is transparent. In more transparent information environment, borrowers are relatively less opaque and banks can easily acquire necessary information about potential loan applicants. In such information environment, the benefits of credit information sharing among banks should be relatively less effective in enhancing bank lending.

Table 2-7 presents the regression results for Equation (2-3). The column 2 and 3 of the table show the regression results for Equation (2-3) which proxies the information environment transparency by the mandatory adoption of IFRS. The coefficient of the interaction term between *DEPTH* and *IFRS* (or β_3 in Equation (2-3)) is negatively significant (at 10% level). Since the value one of the *IFRS* dummy proxies for more transparent information environment, the negative coefficient of the interaction indicates that *IFRS* attenuates the impact of credit information sharing on bank lending. This result supports our hypothesis H2 that the impact of credit information sharing on bank lending is less pronounced in a country with more transparent information environment as proxied by mandatory IFRS adoption.

By evaluating the moderating effect of *IFRS* on the relationship between credit information sharing and bank lending, we find that a one-unit increase of *DEPTH* is associated with an increase of G*LOAN* by 2.5% when the country does not adopt mandatory IFRS. However, when the country adopts mandatory IFRS, a one-unit increase of *DEPTH* will increase *GLOAN* by 2%. Although the coefficient of the interaction term is significant, the magnitude of the moderating impact of *IFRS* on the relationship between *DEPTH* and *GLOAN* is not enormous.

The column 4 and 5 of the same table report the regression results for Equation (2-3) which proxies the information environment transparency by the business extent of disclosure index (BDI). The coefficient of the interaction term between *DEPTH* and *BDI* (or β_3 in Equation (2-3)) is negatively significant (at 5% level). This negative significance of the interaction term suggests that the benefit of credit information sharing in increasing bank lending is lower as *BDI* is higher. Like the result of *IFRS*, the result with *BDI* as a proxy of information environment transparency supports the hypothesis H2 that the impact of credit information sharing on bank lending is less pronounced in a country with more transparent information environment.

The moderating impact of *BDI* on the relationship between *DEPTH* and *GLOAN* is evaluated at the 25th and 75th percentiles of *BDI*. We find that *DEPTH* can increase *GLOAN* by between 2.4% and 2.5%, depending on the degree of *BDI*. Specifically, a unit-increase of *DEPTH* is associated with an increase in *GLOAN* by 2.5% when *BDI* is at the 25th percentile. However, the impact is reduced to 2.4% when *BDI* is at the 75th percentile. Therefore, we can see that there is a moderating effect of BDI on the relationship between credit information sharing and bank lending decision, although the magnitude of such effect is not strong.

2.4.1.3 The Impact of Creditor Rights on the Relationship between Credit Information Sharing and Bank Lending

In this following section, we test how, and to what extent, the protection of creditors affect the relationship between credit information sharing and bank lending. Djankov *et al.* (2007) suggest that better creditor protection through the legal system is a substitute for credit information sharing in fostering credit market expansion. When banks are better protected, banks can more easily force repayment, grab collateral, or even gain control of the firm (Townsend 1979; Aghion & Bolton 1992; Hart & Moore 1994, 1998). As a result, banks are concerned less about the problem of adverse selection and moral hazard and they are more willing to grant loans. Thus, the positive impact of credit information sharing on lending should be less pronounced in countries with strong creditor rights. This prediction is our hypothesis H3.

The regression results for Equation (2-4) are shown in Table 2-8. While the coefficient of *DEPTH* (or β_1 in Equation (2-4)) is positive, it is not significant. The impact of credit information sharing on lending is only significant through its interaction with *CR*. As displayed in Table 2-8, the coefficient of the interaction term between *DEPTH* and *CR* (or β_3 in Equation (2-4)) is negative and significant (at 1% level). The significant interaction term suggests that the impact of credit information sharing on bank lending hinges on the level of creditor rights. At the same time, the negative sign of the interaction term reveals that credit information sharing decreases bank lending when the level of creditor protection is strong.

According to Table 2-8, a one-unit increase of *DEPTH* can decrease *GLOAN* by up to 3.6%, depending on the level of creditor protection. Specifically, when the value of *CR* is

1, a one-unit increase of *DEPTH* decreases loans by 0.9%. For the *CR* value of 2, 3 and 4, a one-unit increase of *DEPTH* reduces loans by 1.8%, 2.7%, and 3.6%, respectively. Remarkably, when the creditor rights are very weak (*CR* = 0), credit information sharing has no notable effect on bank lending. Thus, the negative impact of credit information sharing on lending depends on the level of creditor rights and such negative impact increases with stronger creditor rights.

Overall, our results on Table 2-8 do not support our hypothesis H3. Yet, there are two appealing implications. First, an increase in lending from stronger creditor rights can be reduced with credit information sharing. Due to strong creditor rights, banks have an incentive to extend more loans to a wider (potentially riskier) set of borrowers, regardless of the problem of information asymmetry. At the same time, credit information sharing may prevent such opportunistic behaviors by ensuring that excessive and potentially risky lending is not possible. Moreover, by enhancing borrowers' incentive to repay, credit information sharing may reduce the riskiness of the pool of borrowers, so opportunistic lending is less likely. Second, we can infer from the results that credit information sharing is complementary to creditor rights. Credit information sharing has no value when creditor rights are very weak, but when combined with adequately strong creditor rights, it significantly affects bank lending. This implies that some degree of creditor protection is necessary to guarantee the effect of information sharing on lending.

2.4.2 Robustness Tests

We conduct several robustness tests of our results. First, we proxy the level of credit information sharing in each country by two other measures, consisting of private credit bureau coverages (*PRIV*) and public credit registries coverages (*PUB*). Second, we augment each of Equation (2-2), (2-3) and (2-4) with additional control variables that could potentially influence the volume of bank lending. Third, we provide a subsample analysis for the robustness of our results regarding the hypothesis H2 and H3. Fourth, we provide another subsample analysis by excluding banks in the USA because majorities of banks in the sample comprise of the USA's banks. Lastly, an instrumental variable approach is employed to check for the robustness of the main results.

2.4.2.1 Alternative Measures of Credit Information Sharing

As an alternative to the depth of credit information sharing index, we use private credit bureau coverage (*PRIV*) and public credit bureau coverage (*PUB*) to proxy for the level of credit information sharing in each country. The regression results with *PRIV* is shown in Table 2-9. Noted that higher *PRIV* indicates a higher level of credit information sharing through private credit bureaus. Regarding the hypothesis H1, the result in column 1 still supports that bank lending increases with credit information sharing. Economically, a one-percentage increase in *PRIV* is corresponding to a 0.155% increase in *GLOAN*.

Moreover, the results in column 2 to column 5 show the hypothesis H2 remain consistent with both *IFRS* and *BDI* used as proxies of information asymmetry. Specifically, the coefficient of the interaction term between *IFRS* and *PRIV* is significantly negative. A one-percentage increase of *PRIV* increases bank lending by 0.125% when there is no adoption of IFRS, whereas the one-percentage increase of *PRIV* can increases bank lending by 0.085% when there exists IFRS adoption in a country. Regarding the coefficient of the interaction term between *BDI* and *PRIV*, it is also significantly negative. By evaluating at 25th percentile and 75th percentile of *BDI*, we can see that a one-percentage increase of *PRIV* increases bank lending by 0.148% and 0.139% at 25th percentile and 75th percentile, respectively. Thus, both results with *IFRS* and *BDI* suggest that the impact of credit information sharing on bank lending is less pronounced with more transparent information environment.

We also conduct the sensitivity check for the hypothesis H3. The results are shown in column 6 and column 7. The results are in line with the main results, which are not consistent with the hypothesis H3. The effect of *PRIV* is only significant through its interaction with *CR*. The coefficient of the interaction term between *CR* and *PRIV* is significantly negative suggesting that the impact of *PRIV* on *GLOAN* is negative and more pronounced with higher *CR*. In particular, an one-percentage increase of *PRIV* reduces bank lending 0.012%, 0.024%, 0.036% and 0.048% for the value of *CR* equal to 1, 2, 3 and 4, respectively. However, the impact of *PRIV* has no notable effect on bank lending when the value of *CR* is zero. As stated earlier, the possible explanation is that some degree of creditor protection is needed to encourage banks to extend more credit although costly information asymmetries may have been reduced with more credit information sharing. In addition, when creditor rights are strong, credit information sharing reduces bank lending instead of increasing it by preventing excessive and/or opportunistic lending.

The regression results with *PUB* is shown in Table 2-10. Noted that higher *PUB* means more credit information sharing through public credit registries. The impact of *PUB* on bank lending is found to be insignificant in all models. One possible explanation of the insignificance of *PUB* could be that, as a result of banks' credit information sharing through the public credit registry, the increase in lending to safe borrowers is exactly balanced by the decrease in lending to risky borrowers (Pagano & Jappelli 1993). Another possible explanation is that the public credit registries are developed by bank supervisors as to ensure bank stability by identifying the main debtors of the financial system and analyzing more carefully loan concentration risk (Majnoni *et al.* 2004). With the establishment of the public credit registries, bank supervisors can monitor banks' activities and enforce banks' reserve policies against problem loans. Thus, banks have less ability to lend to risky borrowers and become vigilant when they decide to grant loans.

Generally, a public credit registry has limitations when compared to a private credit bureau. It is quite common for public credit registries to set a minimum loan size and therefore to collect information only on loans in excess of this amount (Miller, 2003). Furthermore, the information from public credit registries consists mainly of credit data and is disseminated in consolidated form (so that details about individual loans are not available). In addition, public registries only collect data from supervised institutions like banks. In contrast, private credit bureaus offer details on individual loans and merge credit data with data from other sources (e.g., firms, leasing and finance companies, retail establishments, courts, tax authorities, and financial statements), though they are less comprehensive in coverage (Jappelli and Pagano, 2002). More importantly, in most cases, historical data are not made available to financial institutions via the public credit registries (Miller, 2003).

2.4.2.2 Additional Control Variables

We control for additional macro factors that could potentially affect bank lending. First, we incorporate a dummy variable indicating the existence of a deposit insurance regime in a country. This dummy is equal to 1 if the country has a deposit insurance regime in a country, while it is equal to zero if the country does not adopt a deposit insurance regime.

Theoretically, deposit insurance schemes are designed to prevent bank runs (when depositors attempt to withdraw their funds all at once) by supporting failing banks with necessary resources (Keeley 1990; Matutes & Vives 1996; Diamond & Dybvig 2000; Demirgüç-Kunt *et al.* 2008). There is also the potential for contagious bank runs on other healthy banks (Allen & Gale 2000). Therefore, many countries enact deposit insurance schemes to improve banking sector stability and reduce the probability of systemic crises (Demirgüç-Kunt & Detragiache 2002).

With deposit insurance, depositors are less concerned about their funds knowing that they will be reimbursed in case banks fail. This reduce the same type of fear that caused the bank run in the 1930s. Banks can increase their risk-taking behavior and willing to extend loans without concerning about the likelihood of bank run. Thus, banks in a country with a deposit insurance regime tend to lend more than in a country without such regime (Diamond & Dybvig 1986; Ivashina & Scharfstein 2010).

Table 2-11 reports the regression results with a deposit insurance dummy (*DEPOSIT_INS*) as one of control factors affecting bank lending. The coefficients of *DEPTH* and its interaction terms with proxies of information asymmetry (*IFRS* and *BDI*) and creditor rights index (*CR*) remain significant across all regression results. Like the main results, *DEPTH* is only significant through its interaction with *CR*. Thus, our main results are still robust with *DEPOSIT_INS* as one of control variables. Looking at the coefficients of *DEPOSIT_INS* across all regression results, we see that some of them are significant. The coefficient of *DEPOSIT_INS* in the baseline regression (column 1) is positive and significant at 10% level, suggesting that there is a significant impact of deposit insurance regime on the volume of bank lending. One possible reason for explaining the insignificance of *DEPOSIT_INS* is that banks may increase risk-taking in non-lending activities.

We also control for the stability of political aspects in a country by including the political stability index (*POLITIC*) from the World Governance Indicators (Kaufmann *et al.* 2011). The index measures perceptions of the likelihood of political instability and/or politically-motivated violence, including terrorism. High values mean more stable political environment. Political instability can affect both supply and demand of loans. On the one hand, when a country is politically unstable, it can have a great impact on investor and consumer confidence and it may make them reluctant to invest in new capital or enter new markets. This would reduce the demand for credit. On the other hand, banks are also reluctant to extend new loans due to political instability and potential political turmoil.

Table 2-12 reports the regression results with political stability index (*POLITIC*) as one of control variable affecting bank lending. The inclusion of *POLITIC* has no effect on our main results. Thus, our main results are still robust with *POLITIC* as one of control variables. Looking at the coefficients of *POLITIC* across all regression results, they are positive and highly significant, suggesting that the stability of political environment is very crucial for bank lending decision.

2.4.2.3 Subsample Analysis

In this section, we provide a subsample analysis. We classify the sample based on each proxy of the information environment. Based on *IFRS* dummy, one subsample consists of observations with *IFRS* proxied for more transparent information environment, while another subsample consists of observations with *NON-IFRS* proxied for low transparent information environment. Based on *BDI*, one subsample consists of observations with the value of *BDI* above the sample median (*HIGH BDI*) to proxy for high transparent information environment, while another subsample consists of observations with the value of *BDI* below the sample median (*LOW BDI*) to proxy for low transparent information environment.

Table 2-13 reports the subsample analysis based on *IFRS* and *BDI.* The subsample with *IFRS* in the column (1) shows that the coefficient of *DEPTH* is positive but not significant, whereas the subsample with *NON-IFRS* in the column (2) shows that the coefficient of *DEPTH* is positive and significant (at 10% level). In comparison to the subsample with *NON-IFRS*, the coefficient of *DEPTH* in the subsample with *IFRS* is not significant at all. This suggests that credit information sharing has an impact on bank risk only in the subsample with *NON-IFRS* adoption. Economically, when there is no adoption of IFRS, a one-unit increase of *DEPTH* is associated with 3.7% increase in lending.

On the same table, the subsample with *HIGH BDI* in the column (3) shows that the coefficient of *DEPTH* is not significant, but the coefficient of *DEPTH* in the subsample with *LOW BDI* shown in the column (4) is significantly positive (at 5% level). This suggests that not only the impact of credit information sharing on bank risk is more pronounced with *LOW BDI*, but such impact is not even significant with *HIGH BDI*. The one-unit increase of *DEPTH* is associated with a 3% increase to lending in the subsample with low BDI. Taken together, our main results related to the hypothesis H2 are still upheld with the subsample analysis based on IFRS and BDI as proxies of information asymmetry.

In addition, we classify the sample based on the creditor rights index. One subsample consists of observations with the value of *CR* above the sample median (*HIGH CR*), while another subsample consists of observations with the value of *CR* below the sample median (*LOW CR*). According to our classification, *HIGH CR* is a group with high creditor rights index, whereas *LOW CR* is a group with low creditor rights index. The last two column on Table 2-13 reports the regression results for each subsample. The coefficients of *DEPTH* are statistically significant in both subsamples.

However, the magnitude of *DEPTH* in the subsample with *LOW CR* is much greater than the subsample with *HIGH CR*. This indicates that the positive impact of *DEPTH* on lending decreases with the level of creditor rights. That is, a one-unit increase of *DEPTH* increases lending by 4.1% in the subsample with low creditor rights index, but its impact on lending decreases to 1.5% in the subsample with high creditor rights index. Thus, our main results are still robust to the subsample analysis based on the creditor rights index.

2.4.2.4 Non-USA Sample

The main results may be driven by banks in the United States of America (USA) because the sample comprises of numerous banks in the USA. Thus, we subsample by excluding banks in the USA and re-estimate each of Equation (2-2), (2-3) and (2-4). The results are shown in Table 2-14. The number of the observation shrinks by almost half. Overall, the results show that exclusion of banks in the USA does not change our main results. We can see that the coefficient of *DEPTH* on column 1 is not only significant but also slightly higher than the one in the main sample.

By evaluating the marginal impact of *DEPTH*, the findings show that a one-unit increase in *DEPTH* is associated with a 4.4% increase in lending, consistent with the hypothesis H1. The hypothesis H2 is also robust. The adoption of IFRS slightly lower the impact of credit information sharing on bank lending. Specifically, when the country does not adopt IFRS, a one-unit increase of *DEPTH* will increase lending by 4.9%. However, when the country adopts IFRS, a one-unit increase of *DEPTH* will increase lending by 4.6%.

Regarding to the moderating impact of *BDI*, we find that a one-unit increase in *DEPTH* is associated with a 3.7% increase in lending at the 25th percentile of *BDI*, while the one-unit increase of *DEPTH* raises lending by 3.3% at the 75th percentile of *BDI*. Our results show that *BDI* has an impact on the relationship between credit information sharing and lending, although the impact of *BDI* is slightly. Furthermore, consistent with the main results, credit information sharing decreases bank lending ranging from 1.2% to 4.8% depending on the value of creditor rights index. Like the main results, credit information sharing has no notable impact on lending when the credit rights index is zero.

2.4.2.5 Instrumental Variable Approach

We perform an instrumental variable approach to avoid any potential endogeneity problem that could exist due to the reverse causality between credit information sharing and bank lending[7]. We select the instrumental variables based on the existing literature on law and finance (Easterly & Levine 1997; LaPorta *et al.* 1998; La Porta *et al.* 1999; Beck *et al.* 2003; Acemoglu & Johnson 2005). Specifically, we employ legal origins, ethnic fractionalization, and latitude as instrumental variables for *DEPTH*[8]. They are previously used in Barth *et al.* (2009), Houston *et al.* (2010), Büyükkarabacak and Valev (2012) and Fu *et al.* (2014) as instruments. Because our instruments consist of time-invariant variables, we use a two-stage least square (2SLS) with pooled OLS estimations rather than fixed effects estimations.

To test for the endogeneity of *DEPTH*, we perform the Durbin-Wu-Hausman test of endogeneity. The Durbin-Wu-Hausman tests for endogeneity in a regression estimated with IV approach, the null hypothesis for which states that an OLS estimator of the same equation would yield consistent estimates: that is, any endogeneity among the regressors would not

[7] The reverse causality between credit information sharing and bank lending is less problematic in our study because we investigate the effect of credit information sharing agencies on the volume of bank lending of individual bank firms.

[8] Refer to Appendix G for the rationales behind selecting instruments

have harmful effects on OLS estimates (Durbin 1954; Wu 1974; Hausman 1978; Baum *et al.* 2007). A rejection of the null indicates that the effects of endogenous regressors on the estimates are meaningful, and instrumental variables approaches are necessary. This rejection means that *DEPTH* can be treated as exogenous under the null hypothesis. After we perform the Durbin-Wu-Hausman tests for endogeneity, the estimation shows that the p-value is 0.7816 so the null hypothesis cannot be rejected. Thus, we can treat depth of credit information sharing as exogenous. Nonetheless, we perform robustness tests for Equation (2-2) to (2-4) by employing an instrumental variable approach. The results are presented in Table 2-15, Table 2-16 and Table 2-17.

To test for the relevance and validity of the instruments of the credit information sharing, we perform the First Stage F-test and the Hansen's J test. Specifically, with regards to the relevance of these instruments, we conduct an F-test of the excluded instruments in the corresponding first-stage regression. The null hypothesis of the test is that the instruments do not explain cross-sectional differences in the credit information measure. On all tables, we reject the null hypothesis at the 1% level in all regressions. In addition, the Hansen J-test of over-identifying restrictions cannot be rejected suggesting that the instruments are valid instruments, uncorrelated with the error term and correctly excluded from the estimated equation[9].

As we have confirmed the relevance and validity of our instruments, we continue to analyze the IV regression results of each table. First, we analyze the IV regression results for Equation (2-2). On Table 2-15, the first column reports the second stage regression, while the second column reports the first stage regression. The main result is still robust and consistent with our first hypothesis H1. The coefficient of *DEPTH* remains positive and significant. The result with IV approach confirms our main finding that bank lending increases with credit information sharing. Moreover, the IV coefficient is much larger than the coefficient of the fixed effect regression, indicating the presence of potential measurement error, which inflates the IV coefficient. Nonetheless, our conclusion does not

[9] By confirming the relevance and validity of our instruments, we are not claiming that these variables are the best instrumental variables, but we hold that these instruments are reasonably exogenous and have adequate explanatory power for the credit information sharing measure

depend on the instrumentation approach because *DEPTH* is not endogenous and poses no concern of endogeneity.

For Equation (2-3) and (2-4), we split the sample into two subsamples based on each of information environment proxies and the creditor rights index. The regression results of Equation (2-3) are reported in Table 2-16. The first four columns of Table 2-16 present the IV regressions of two subsamples that are split based on *IFRS* as a proxy of information environment transparency. The results are robust and consistent with our second hypothesis H2. The coefficient of *DEPTH* is only significant in the subsample without the mandatory IFRS adoption suggesting that the impact of credit information sharing on bank lending is more pronounced when the information environment is less transparent. Similar results are applied to the subsample based on *BDI*. In column 5 to column 8 of Table 2-16, the coefficient of *DEPTH* is only significant in the subsample with *LOW BDI* suggesting that the impact of credit information sharing on bank lending is more pronounced when the information environment is less transparent.

Regarding Equation (2-4), Table 2-17 presents the IV regressions of two subsamples which are split based on the value of creditor rights index. The value of creditor rights index above the median value of the sample is corresponded to the high level of creditors' protection (*HIGH CR*), while the value of creditor rights index below the median value of the sample corresponds to the low level of creditors' protection (*LOW CR*). The coefficient of *DEPTH* is positive and significant only in the subsample with *LOW CR*. This result does not pose a serious problem to our main results because our IV approach is based on pooled OLS estimations rather than fixed effects estimations. With pooled OLS estimations, the estimates may be biased and inefficient.

2.5 Conclusion

This chapter attempts to examine the relationship between credit information sharing and bank lending of 16,009 banks in 113 countries during the period of 2005 – 2013. The theory makes no clear-cut predictions about the impact of information sharing on the volume of bank lending. Therefore, we provide an analysis by employing a bank-level data around the globe. Unlike previous studies, we provide bank-level lending (supply side) evidence, which is consistent with theoretical predictions of credit information sharing in credit markets.

The results show that credit information sharing has a positive impact on bank lending. This finding is consistent with theoretical analyses supporting that credit information sharing promotes bank lending. Since credit information sharing facilitates lending decision, banks tend to provide more credits in countries with more credit information sharing. With more information sharing, banks are more willing to lend as the asymmetric information between banks and borrowers are less problematic.

Moreover, we examine the impact of information environment on the relationship between credit information sharing and bank lending. We proxy the transparency of the information environment by mandatory IFRS adoption and the extent of business disclosure. The results reveal that the positive association between credit information sharing and bank lending is less pronounced in countries with mandatory IFRS adoption and greater extent of business disclosure. When the information environment is more transparent, borrower information is plentifully available and accessible to the public. Therefore, the positive impact of credit information sharing on bank lending tends to be less pronounced with more transparent information environment.

We also explore whether the impact of credit information sharing on bank lending varies with the level of creditor protection. We find that credit information sharing only affects bank lending through its interaction with creditor rights index. Our finding shows that credit information sharing reduces bank lending in countries with well-protected creditors, while it has no notable effect on bank lending in countries with low creditor protection. From this finding, we can infer that credit information sharing reduce an increase in lending from stronger creditor protection. Furthermore, we can infer that credit information sharing is complementary to creditor rights, such that some degree of creditor protection is required to guarantee the effect of information sharing on lending.

Our results are robust to additional country-level control variables, subsample analysis, non-USA sample and an instrumental variable approach. The exception is the robustness test with alternative measures of credit information sharing. While we find that bank lending increases with information sharing through private credit bureaus, there is no significant impact of information sharing through public credit registries on bank lending. The possible explanation may be because the increase in lending to safe borrowers matches the decrease to risky borrowers (Pagano & Jappelli 1993). Another possible explanation is that public credit registries are developed by bank supervisors to monitor bank activities by ensuring bank stability (Majnoni *et al.* 2004).

Figure 2-1: Diagram for Research Question 1

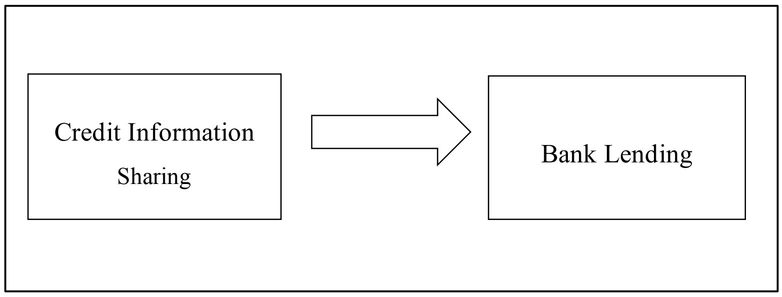

Figure 2-2: Diagram for Research Question 2

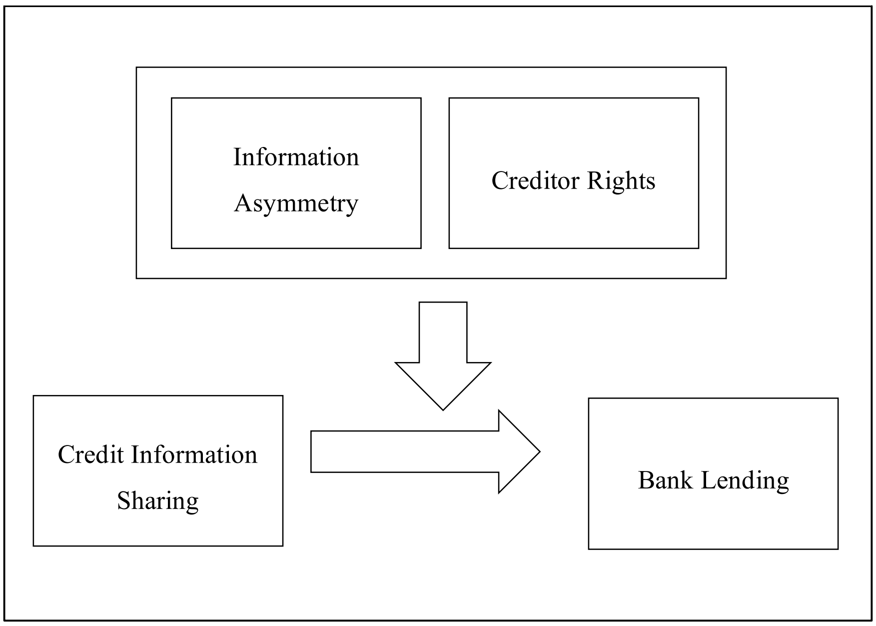

Table 2-1: Summary of Variables, Symbols and Sources

Variable			Description	Original Sources
Dependent Variable	GLOAN	Growth of Gross Loans	The change of the natural logarithm of total amount of loans to households and firms (billion US dollars). It is calculated as the difference between the natural logarithm of gross loans in current period and the natural logarithm of gross loans in previous period. $GLOAN_{i,t} = log[LOAN_{i,t}] - log[LOAN_{i,t-1}]$ *Higher (lower) value indicates higher (lower) bank lending*	BankScope
Explanatory Variables	DEPTH	Depth of Credit Information Sharing index	An index that measures the scope and contents of credit information that being shared. It ranges from zero to six. The value of zero indicates that there is no public credit registry or private credit bureau operating in a country. The value of one is added to the index with each of the following characteristics: • Both positive and negative information are distributed. • Data on households and firms are distributed. • Data from retailers, trade creditors, and/or utility companies as well as financial institutions are distributed. • More than 2 years of data are available. • Data are collected and distributed on loans with value below 1% of income per capita. • Laws give right to borrowers to inspect their own data. *Higher (lower) DEPTH indicates more (lower) credit information sharing level*	World Bank's Doing Business
	PRIV	Private Credit Bureau Coverage (%)	This variable reports the number of individuals and firms listed in private credit bureau's database with information on repayment, unpaid debt or credit outstanding from the past five years. The number is expressed as a percentage of the adult population (the population age 15 and above according to the World Development Indicators). If no private bureau operates, the coverage value is 0%. *Higher (lower) PRIV indicates more (lower) credit information sharing level (through private credit bureaus)*	World Bank's Doing Business
	PUB	Public Credit Registry Coverage (%)	This variable reports the number of individuals and firms listed in public credit registry's database with information on repayment, unpaid debt or credit outstanding from the past five years. The number is expressed as a percentage of the adult population (the population age 15 and above according to the	World Bank's Doing Business

			World Development Indicators). If no public registry operates, the coverage value is 0%. *Higher (lower) PUB indicates more (lower) credit information sharing level (through public credit registries)*	
	IFRS	International Financial Reporting Standard (IFRS)	A dummy variable whose value is equal to 1 for a country (and year) that adopts IFRS and 0 otherwise. *A value of one (zero) indicates more (less) transparent information environment.*	"IFRS foundation and IASB", Deloitte and Simon Fraser University in Canada
	BDI	Business Extent of Disclosure Index (BDI)	This index measures the extent to which investors are protected through disclosure of ownership and financial information (World Bank's Doing Business 2016). It ranges from 0 to 10 with higher value indicating more disclosure of ownership and financial information to investors. *Higher (lower) index indicates more (less) transparent information environment.*	World Bank's Doing Business
	CR	Creditor Right index	An aggregate measure of creditor legal protection created based on the methodology proposed by LaPorta *et al.* (1998). The index is ranging from zero to four. The index consists of 4 components: • Restrictions on reorganization: whether there are restrictions imposed, such as creditors' consent or minimum divided, when a debtor files for reorganization. • No automatic stay: whether secured creditors are able to gain possession of assets after the petition for reorganization is approved, that is, whether there is no automatic stay or asset freeze imposed by the court on a creditor's ability to seize collateral. • Secured creditor paid first: whether secured creditors are ranked first in the distribution of proceeds of liquidating a bankrupt firm as opposed to other creditors such as government or workers • No management stay: whether the incumbent management does not stay in control of the firm during the reorganization, in other words, whether an administrator, not the management, is responsible for running the business during the reorganization A value of one is added to the index when a country's laws and regulations provide each of these powers to secured lenders. Higher index indicates that secured lenders are better protected in case a borrower defaults.	LaPorta *et al.* (1998); Djankov *et al.* (2007)

			Higher (lower) index indicates greater (less) protection of creditors	
Bank-Specific Variables	SIZE	Bank Size	The logarithm of bank's assets (billion US dollars)	BankScope
	NIM	Net Interest Margin	Accounting value of bank's net interest revenue as a share of its interest-bearing (total earning) assets. It tracks the profitability of a bank's investing and lending activities.	BankScope
	EFFICIENCY	Cost-to-Income Ratio	This is a ratio of the overhead (or cost of running the bank) to operating income (interest and non-interest income), which reflects operations on both on and off balance sheet. This measures the bank's efficiency. Overheads is data2090; Interest income is data2080; Non-interest income is data2085. This is similar to data4029 in BankScope.	BankScope
	DEP	Deposit to Asset	This is a ratio of total deposits to total bank assets. Total deposits include total customer deposits (data11550), deposits of governments and municipalities (data38382) and deposits from banks (data11560)	BankScope
	LLR	Loan Loss Reserves to Gross Loans Ratio	It is a ratio of total loan loss reserves (data2070 or data11080) to total gross loans (data2001 or data11100). This measure a reserve for losses expressed as percentage of total loans. The ratio is equivalent to data4001 or data18205 in Bankscope.	BankScope
Country-Specific Variables	GDPG	A growth rate of gross domestic products (GDP)	This variable is a growth rate of GDP. It captures macroeconomic developments and a proxy for fluctuation in economic activities.	World Development Indicators (WDI)
	INF	Inflation	This inflation variable is proxied by the consumer price index (CPI). It links to the fluctuation of price movement and higher inflation is associated with high nominal interest, reflecting poor macroeconomic management.	World Development Indicators (WDI)
	CCT3	Bank Concentration Ratio	Assets of three largest banks as a share of total banking assets. Total assets include total earning assets, cash and due from banks, foreclosed real estate, fixed assets, goodwill, other intangibles, current tax assets, deferred tax assets, discontinued operations and other assets.	World Bank's Global Financial Development database; BankScope
	CAPITAL_STR	Capital Stringency Index	This is an index measuring the extent of both initial and overall capital stringency. The index ranges from 0 to 10. This index is constructed from following questions: 1. Whether the minimum capital-asset ratio requirement is in line with the Basel Committee on Banking Supervision guidelines	World Bank's *Bank Regulation and Supervision*

			2. Does the minimum ratio varies as a function of an individual bank's credit risk? 3. Does the minimum ratio varies as a function of an individual bank's market risk? 4. Before minimum capital adequacy is determined, which of the following are deducted from the book value of capital: a. Market value of loan losses not realized in accounting books? b. Unrealized losses in securities portfolios? c. Unrealized foreign exchange losses? 5. What fraction of revaluation gains is allowed as part of capital? (1 if the fraction is less than 0.75 and 0 otherwise) 6. Are the sources of funds to be used as capital verified by the regulatory/supervisory authorities? 7. Can the initial disbursement or subsequent injections of capital be done with assets other than cash or government securities? 8. Can initial capital contributions by prospective shareholders be in the form of borrowed funds?	
	DEPOSIT_INS	Deposit Insurance Dummy	A dummy variable indicating if the country had or not explicit deposit insurance system and zero otherwise.	Barth *et al.* (2006); Barth *et al.* (2013a)
	POLITIC	Political Stability Index	The indicator measures the perceptions of the likelihood that the government will be destabilized or overthrown by unconstitutional or violent means, including political violence and terrorism. The value of year 2005 is used in this study. Higher values mean more stable political environment.	World Bank's Governance Indicators by Kaufmann *et al.* (2009)
Instrumental Variables	LEGALORIGIN	Legal Origin	A dummy variable whose value is equal to one if a country has English legal origin and otherwise zero.	Djankov *et al.* (2007)
	ETHNIC_FRAC	Ethnic fractionalization	This variable captures the ethnic diversity in a country. It measures probability that two randomly selected people from a given country will not belong to the same ethnolinguistic group.	Easterly (2001)
	LATITUDE	Latitude	This variable measures the geographical latitude of a country. It is calculated as an absolute value of the latitude of the country scaled to take a value between zero and one	La Porta *et al.* (1999); Central Intelligence Agency (CIA)

Table 2-2: Descriptive Statistics

		Variable	Obs.	Mean	Stdev.	Min	Max	P25	P50	P75
Dependent variable		***GLOAN***	99,680	0.089	0.301	-8.510	9.410	-0.021	0.052	0.142
Explanatory variables	**CIS**	***DEPTH***	99,680	5.010	1.100	0.000	6.000	4.000	5.000	6.000
		PRIV	99,680	0.788	0.357	0.000	1.000	0.678	1.000	1.000
		PUB	99,680	0.098	0.110	0.000	1.000	0.000	0.0270	0.241
	ASYM	***IFRS***	99,680	0.305	0.460	0.000	1.000	0.000	0.000	1.000
		BDI	99,680	6.420	1.770	0.000	10.000	6.000	7.000	7.000
		CR	99,680	1.540	0.880	0.000	4.000	1.000	1.000	2.000
Bank-specific Control		***SIZE***	99,680	5.740	2.160	-6.250	20.400	4.510	5.510	6.760
		NIM	99,680	0.040	0.040	-3.700	3.520	0.026	0.036	0.045
		EFFICIENCY	99,680	0.716	0.377	0.000	9.890	0.578	0.677	0.783
		DEP	99,680	0.783	0.197	0.000	2.750	0.749	0.844	0.895
		LLR	99,680	0.025	0.042	-0.063	0.995	0.010	0.015	0.024
Country-specific Controls		***GDPG***	99,680	0.020	0.029	-0.148	0.226	0.009	0.022	0.034
		INF	99,680	0.031	0.045	-0.251	1.040	0.012	0.020	0.031
		CCT3	99,680	0.428	0.176	0.073	1.000	0.322	0.351	0.548
		CAPITAL_STR	99,680	6.830	1.350	0.000	8.000	6.000	7.000	8.000
		DEPOSIT_INS	99,680	0.961	0.193	0.000	1.000	1.000	1.000	1.000
		POLITIC	99,680	0.397	0.593	-2.500	1.590	0.374	0.502	0.635
Instrumental Variables		***LEGALORIGIN***	99,680	0.587	0.492	0.000	1.000	0.000	1.000	1.000
		ETHNIC_FRAC	92,795	0.375	0.220	0.000	0.930	0.100	0.500	0.500
		LATITUDE	98,793	0.700	0.082	0.295	0.835	0.691	0.691	0.763

This table presents descriptive statistics of variables. *GLOAN* is the change of the natural logarithm of total gross loans in current year and previous year; *CIS* represents credit information sharing measures; *DEPTH* is depth of credit information sharing index; *PRIV* is private credit bureau coverage (% of adult population); *PUB* is public credit registry coverage (% of adult population); *ASYM* represents information environment proxies; *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *BDI* is a business extent of disclosure index; *CR* is a creditor rights index; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *NIM* is a net interest margin; *EFFICIENCY* is a cost-to-income ratio; *DEP* is a ratio of total deposits to total assets; *LLR* is a ratio of loan loss reserves to gross loans; *GDPG* is a growth rate of GDP; *INF* is inflation; *CCT3* is a concentration index calculated from the fraction of assets held by the 3 largest banks in a country: *CAPITAL_STR* is a capital stringency index measuring the extent of both initial and overall capital stringency in a country; *DEPOSIT_INS* is a dummy for deposit insurance taking a value of one if the country has adopted a deposit insurance regime, and zero otherwise; *POLITIC* is a political stability index; *LEGALORIGIN* is dummy variable whose value is equal to one if a country has English legal origin and otherwise zero; *ETHNIC_FRAC* is an ethnic fractionalization which captures the ethnic diversity in a country; *LATITUDE* is a latitude which measures the geographical latitude of a country. Further detail of all variables is presented in Table 2-1 in this chapter. Obs is observation. Stdev is for standard deviation. Min is minimum. Max is maximum. P25 is 25th percentile of the sample. P50 is 50th percentile (or median) of the sample. P75 is 75th percentile of the sample

Table 2-3: Pearson Correlation Matrix

Variable	*GLOAN*	*DEPTH*	*PRIV*	*PUB*	*IFRS*	*BDI*	*CR*	*SIZE*	*NIM*	*COST*
GLOAN	1.000									
DEPTH	0.208	1.000								
PRIV	0.164	0.730	1.000							
PUB	-0.049	-0.327	-0.534	1.000						
IFRS	0.043	-0.298	-0.416	0.674	1.000					
BDI	0.037	-0.133	-0.354	-0.257	-0.348	1.000				
CR	0.041	-0.184	-0.417	0.463	0.447	-0.489	1.000			
SIZE	0.061	-0.204	-0.254	0.361	0.413	-0.144	0.265	1.000		
NIM	0.109	0.054	0.167	-0.284	-0.415	0.161	-0.307	-0.368	1.000	
COST	-0.137	0.189	0.149	-0.111	-0.074	-0.024	-0.065	-0.256	-0.036	1.000
DEP	-0.167	0.421	0.271	-0.131	-0.063	0.021	-0.022	-0.128	-0.037	0.138
LLR	-0.027	-0.200	-0.266	0.219	0.163	-0.116	0.168	0.326	0.026	-0.100
GDPG	0.226	-0.213	-0.275	0.038	-0.083	-0.135	0.095	-0.034	0.183	-0.137
INF	0.295	-0.268	-0.121	-0.091	-0.172	0.093	-0.064	-0.109	0.379	-0.131
CCT3	0.001	-0.082	-0.329	0.338	0.454	-0.456	0.463	0.211	-0.261	-0.058
CAPITAL_STR	-0.231	0.446	0.687	-0.433	-0.413	0.351	-0.489	-0.217	0.189	0.174
DEPOSIT_INS	-0.119	0.290	0.288	-0.175	-0.001	0.036	-0.092	-0.071	-0.064	0.115
POLITIC	-0.168	0.215	0.070	0.076	0.359	-0.288	0.230	0.170	-0.449	0.078
LEGALORIGIN	-0.085	0.530	0.718	-0.706	-0.673	0.531	-0.593	-0.337	0.374	0.095
ETHNIC_FRAC	0.057	0.092	0.333	-0.606	-0.751	0.403	-0.628	-0.296	0.466	0.015
LATITUDE	-0.065	-0.174	-0.282	0.271	0.594	-0.326	0.460	0.259	-0.458	0.029

This table presents a (Pearson) correlation matrix of variables. *GLOAN* is the change of the natural logarithm of total gross loans in current year and previous year; *CIS* represents credit information sharing measures; *DEPTH* is depth of credit information sharing index; *PRIV* is private credit bureau coverage (% of adult population); *PUB* is public credit registry coverage (% of adult population); *ASYM* represents information environment proxies; *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *BDI* is a business extent of disclosure index; *CR* is a creditor rights index; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *NIM* is a net interest margin; *EFFICIENCY* is a cost-to-income ratio; *DEP* is a ratio of total deposits to total assets; *LLR* is a ratio of loan loss reserves to gross loans; *GDPG* is a growth rate of GDP; *INF* is inflation; *CCT3* is a concentration index calculated from the fraction of assets held by the 3 largest banks in a country: *CAPITAL_STR* is a capital stringency index measuring the extent of both initial and overall capital stringency in a country; *DEPOSIT_INS* is a dummy for deposit insurance taking a value of one if the country has adopted a deposit insurance regime, and zero otherwise; *POLITIC* is a political stability index; *LEGALORIGIN* is dummy variable whose value is equal to one if a country has English legal origin and otherwise zero; *ETHNIC_FRAC* is an ethnic fractionalization which captures the ethnic diversity in a country; *LATITUDE* is a latitude which measures the geographical latitude of a country.

Table 2-4: Pearson Correlation Matrix (Continued)

Variable	***DEP***	***LLR***	***GDPG***	***INF***	***CCT3***	***CAPITAL_STR***	***DEPOSIT_INS***	***POLITIC***	***LEGALORIGIN***	***ETHNIC_FRAC***	***LATITUDE***
DEP	1.000										
LLP	-0.114	1.000									
GDPG	-0.100	-0.037	1.000								
INF	-0.290	-0.071	0.426	1.000							
CCT3	0.101	0.142	-0.042	-0.086	1.000						
CAPITAL_STR	0.233	-0.122	-0.410	-0.300	-0.389	1.000					
DEPOSIT_INS	0.070	-0.097	-0.240	-0.225	-0.163	0.238	1.000				
POLITIC	0.315	-0.048	-0.241	-0.527	0.460	0.068	0.194	1.000			
LEGALORIGIN	0.204	-0.228	-0.096	0.092	-0.441	0.629	0.102	-0.255	1.000		
ETHNIC_FRAC	-0.013	-0.137	0.130	0.308	-0.447	0.387	-0.096	-0.472	0.771	1.000	
LATITUDE	-0.014	0.024	-0.166	-0.307	0.119	-0.244	0.313	0.493	-0.603	-0.697	1.000

This table presents a (Pearson) correlation matrix of variables. *GLOAN* is the change of the natural logarithm of total gross loans in current year and previous year; *CIS* represents credit information sharing measures; *DEPTH* is depth of credit information sharing index; *PRIV* is private credit bureau coverage (% of adult population); *PUB* is public credit registry coverage (% of adult population); *ASYM* represents information environment proxies; *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *BDI* is a business extent of disclosure index; *CR* is a creditor rights index; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *NIM* is a net interest margin; *EFFICIENCY* is a cost-to-income ratio; *DEP* is a ratio of total deposits to total assets; *LLR* is a ratio of loan loss reserves to gross loans; *GDPG* is a growth rate of GDP; *INF* is inflation; *CCT3* is a concentration index calculated from the fraction of assets held by the 3 largest banks in a country: *CAPITAL_STR* is a capital stringency index measuring the extent of both initial and overall capital stringency in a country; *DEPOSIT_INS* is a dummy for deposit insurance taking a value of one if the country has adopted a deposit insurance regime, and zero otherwise; *POLITIC* is a political stability index; *LEGALORIGIN* is dummy variable whose value is equal to one if a country has English legal origin and otherwise zero; *ETHNIC_FRAC* is an ethnic fractionalization which captures the ethnic diversity in a country; *LATITUDE* is a latitude which measures the geographical latitude of a country. Further detail of all variables is presented in Table 2-1 in this chapter.

Table 2-5: Model Selection and Diagnostic Tests

Panel A: Poolability Test

F(16818, 98607)	40.07
F(16818, 98607) P-value	0.00

The test of poolability is performed to determine the presence of individual effects, α_i in the regression model. H_0: α_i=0 for i = 1, 2, 3…., N. The rejection of the null hypothesis indicates that the individual effects exist and the OLS estimates suffer from the problem of omitted variables.

Panel B: Hausman Test

Chi-sq(10)	1135.86
Chi-sq(10) P-value	0.00

The Hausman test is performed to choose between the fixed effect model and the random effect model. H_0: difference in coefficients not systemic. The rejection of the null hypothesis indicates that the fix effect regression model is preferable to the random effect.

Panel C: Modified Wald Test for Groupwise Heteroskedasticity in Fixed Effect Regression Model

Chi-sq(16819)	393.4
Chi-sq(16819) P-value	0.00

The modified Wald test is performed to test for the presence of groupwise heteroskedasticity in the residuals. H_0: $\sigma_i^2 = \sigma^2$ for i = 1, 2, 3…., Ng, where Ng is the number of cross-sectional units. The rejection of the null hypothesis indicates that there exist the groupwise geteroskedasticity.

Panel D: Wooldridge Test for Autocorrelation in Panel Data

F(1, 14657)	506.629
F(1, 14657) P-value	0.00

The Wooldridge test is performed to test for the presence of serial correlation. H_0: no first-order autocorrelation. The rejection of the null hypothesis indicates that data does not have first-order autocorrelation.

Table 2-6: The Impact of Credit Information Sharing on Bank Lending

Variable	GLOAN
	(1)
DEPTH	0.023*
	(1.94)
SIZE	0.110***
	(3.53)
NIM	0.504**
	(2.03)
EFFICIENCY	-0.054***
	(-3.71)
DEP	-0.011
	(-0.11)
LLR	-0.029***
	(-2.65)
GDPG	1.574***
	(4.19)
INF	0.093
	(0.39)
CCT3	0.048
	(0.69)
CAPITAL_STR	-0.012**
	(-2.24)
Constant	-0.410*
	(-1.69)
R-squared	0.274
Bank Fixed Effects	Yes
Time Dummies	Yes
Observations	99,680

The table presents the regression result for the impact of credit information sharing on bank lending. The dependent variable is bank lending measured by GLOAN. *GLOAN* is the change of the natural logarithm of total gross loans in current year and previous year; *DEPTH* is depth of credit information sharing index; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *NIM* is a net interest margin; *EFFICIENCY* is a cost-to-income ratio; *DEP* is a ratio of total deposits to total assets; *LLR* is a ratio of loan loss reserves to gross loans; *GDPG* is a growth rate of GDP; *INF* is inflation; *CCT3* is a concentration index calculated from the fraction of assets held by the 3 largest banks in a country: *CAPITAL_STR* is a capital stringency index measuring the extent of both initial and overall capital stringency in a country. Further detail of all variables is presented in Table 2-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 2-7: The Impact of Credit Information Sharing on Bank Lending: The Role of Information Asymmetry

Variable	GLOAN				
	(1)	(2)	(3)	(4)	(5)
DEPTH	0.023*	0.023**	0.025**	0.023*	0.031**
	(1.94)	(2.36)	(2.04)	(1.92)	(2.83)
IFRS		0.09**	0.06*		
		(2.33)	(1.78)		
IFRS * DEPTH			-0.005*		
			(-1.70)		
BDI				0.007**	0.006*
				(2.23)	(1.90)
BDI * DEPTH					-0.001**
					(-2.22)
SIZE	0.110***	0.114***	0.114***	0.110***	0.110***
	(3.53)	(3.51)	(3.51)	(3.50)	(3.49)
NIM	0.504**	0.487*	0.487*	0.504**	0.504**
	(2.03)	(1.87)	(1.87)	(2.03)	(2.03)
EFFICIENCY	-0.054***	-0.054***	-0.054***	-0.054***	-0.054***
	(-3.71)	(-3.83)	(-3.82)	(-3.72)	(-3.72)
DEP	-0.011	-0.017	-0.017	-0.011	-0.011
	(-0.11)	(-0.18)	(-0.18)	(-0.11)	(-0.11)
LLR	-0.029***	-0.029***	-0.029***	-0.029***	-0.029***
	(-2.65)	(-2.66)	(-2.66)	(-2.65)	(-2.65)
GDPG	1.574***	1.546***	1.544***	1.574***	1.567***
	(4.19)	(4.12)	(4.09)	(4.17)	(4.13)
INF	0.093	0.080	0.081	0.093	0.094
	(0.39)	(0.34)	(0.34)	(0.39)	(0.39)
CCT3	0.048	0.038	0.039	0.048	0.049
	(0.69)	(0.53)	(0.54)	(0.69)	(0.69)
CAPITAL_STR	-0.012**	-0.012**	-0.012**	-0.012**	-0.012**
	(-2.24)	(-2.28)	(-2.27)	(-2.23)	(-2.14)
Constant	-0.410*	-0.389	-0.392	-0.404*	-0.375
	(-1.69)	(-1.58)	(-1.59)	(-1.70)	(-1.47)
R-squared	0.274	0.275	0.275	0.274	0.274
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes
Observations	99,680	99,680	99,680	99,680	99,680

The table presents the regression results for the impact of information asymmetry on the relationship between credit information sharing and bank lending. The dependent variable is bank lending measured by GLOAN. *GLOAN* is the change of the natural logarithm of total gross loans in current year and previous year; *DEPTH* is depth of credit information sharing index; *IFRS* and *BDI* are proxies of information environment; *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *BDI* is a business extent of disclosure index; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *NIM* is a net interest margin; *EFFICIENCY* is a cost-to-income ratio; *DEP* is a ratio of total deposits to total assets; *LLR* is a ratio of loan loss reserves to gross loans; *GDPG* is a growth rate of GDP; *INF* is inflation; *CCT3* is a concentration index calculated from the fraction of assets held by the 3 largest banks in a country: *CAPITAL_STR* is a capital stringency index measuring the extent of both initial and overall capital stringency in a country. Further detail of all variables is presented in Table 2-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 2-8: The Impact of Credit Information Sharing on Bank Lending - The Role of Creditor Rights

Variable	GLOAN		
	(1)	(2)	(3)
DEPTH	0.023*	0.023**	0.07
	(1.94)	(2.07)	(1.30)
CR		0.01**	0.045***
		(2.27)	(3.43)
CR * DEPTH			-0.009***
			(-3.79)
SIZE	0.110***	0.110***	0.110***
	(3.53)	(3.53)	(3.52)
NIM	0.504**	0.504**	0.505**
	(2.03)	(2.03)	(2.03)
EFFICIENCY	-0.054***	-0.054***	-0.054***
	(-3.71)	(-3.71)	(-3.74)
DEP	-0.011	-0.011	-0.009
	(-0.11)	(-0.11)	(-0.09)
LLR	-0.029***	-0.029***	-0.029***
	(-2.65)	(-2.65)	(-2.65)
GDPG	1.574***	1.574***	1.558***
	(4.19)	(4.19)	(4.17)
INF	0.093	0.093	0.135
	(0.39)	(0.39)	(0.56)
CCT3	0.048	0.048	0.054
	(0.69)	(0.69)	(0.77)
CAPITAL_STR	-0.012**	-0.012**	-0.012**
	(-2.24)	(-2.24)	(-2.24)
Constant	-0.410*	-0.410*	-0.488*
	(-1.69)	(-1.69)	(-1.96)
R-squared	0.274	0.274	0.274
Bank Fixed Effects	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes
Observations	99,680	99,680	99,680

The table presents the regression results for the impact of creditor rights on the relationship between credit information sharing and bank lending. The dependent variable is bank lending measured by GLOAN. *GLOAN* is the change of the natural logarithm of total gross loans in current year and previous year; *DEPTH* is depth of credit information sharing index; *CR* is a creditor rights index; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *NIM* is a net interest margin; *EFFICIENCY* is a cost-to-income ratio; *DEP* is a ratio of total deposits to total assets; *LLR* is a ratio of loan loss reserves to gross loans; *GDPG* is a growth rate of GDP; *INF* is inflation; *CCT3* is a concentration index calculated from the fraction of assets held by the 3 largest banks in a country: *CAPITAL_STR* is a capital stringency index measuring the extent of both initial and overall capital stringency in a country. Further detail of all variables is presented in Table 2-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

* indicates significance at the 10% level

** indicates significance at the 5% level

*** indicates significance at the 1% level

Table 2-9: Estimation Results with Alternative Proxy of Credit Information Sharing - Private Credit Bureau Coverages

Variable	GLOAN						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PRIV	0.155*	0.150**	0.125**	0.153**	0.202**	0.155**	0.183
	(1.92)	(2.06)	(2.03)	(2.04)	(2.13)	(2.22)	(1.53)
IFRS		0.109***	0.068*				
		(5.74)	(1.74)				
IFRS * PRIV			-0.04**				
			(-2.72)				
BDI				0.010**	0.013		
				(2.22)	(0.95)		
BDI * PRIV					-0.009*		
					(-1.69)		
CR						0.015**	0.07***
						(2.27)	(3.43)
CR * PRIV							-0.012**
							(-2.24)
SIZE	0.101***	0.105***	0.106***	0.101***	0.101***	0.101***	0.104***
	(3.77)	(3.73)	(3.71)	(3.74)	(3.74)	(3.77)	(3.64)
NIM	0.490*	0.473*	0.468*	0.490*	0.490*	0.490*	0.478*
	(1.93)	(1.78)	(1.76)	(1.93)	(1.93)	(1.93)	(1.87)
EFFICIENCY	-0.051***	-0.052***	-0.052***	-0.051***	-0.051***	-0.051***	-0.052***
	(-3.24)	(-3.34)	(-3.36)	(-3.25)	(-3.27)	(-3.24)	(-3.38)
DEP	-0.003	-0.008	-0.009	-0.003	-0.003	-0.003	-0.008
	(-0.03)	(-0.08)	(-0.09)	(-0.03)	(-0.03)	(-0.03)	(-0.08)
LLR	-0.029***	-0.029***	-0.029***	-0.029***	-0.029***	-0.029***	-0.029***
	(-2.66)	(-2.66)	(-2.66)	(-2.66)	(-2.66)	(-2.66)	(-2.65)
GDPG	1.641***	1.614***	1.634***	1.640***	1.637***	1.641***	1.606***
	(4.28)	(4.18)	(4.17)	(4.25)	(4.26)	(4.28)	(4.06)
INF	0.067	0.054	0.035	0.066	0.067	0.067	0.046
	(0.26)	(0.21)	(0.14)	(0.26)	(0.26)	(0.26)	(0.19)
CCT3	0.066	0.056	0.053	0.065	0.067	0.066	0.062
	(0.88)	(0.73)	(0.67)	(0.87)	(0.89)	(0.88)	(0.84)
CAPITAL_STR	-0.009*	-0.009**	-0.008*	-0.009*	-0.009*	-0.009*	-0.009*
	(-1.94)	(-2.03)	(-1.79)	(-1.95)	(-1.91)	(-1.94)	(-1.92)
Constant	-0.515**	-0.496**	-0.439*	-0.496**	-0.489**	-0.515**	-0.434*
	(-2.16)	(-2.05)	(-1.80)	(-2.11)	(-2.12)	(-2.16)	(-1.84)
R-squared	0.272	0.273	0.273	0.272	0.272	0.272	0.273
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	99,680	99,680	99,680	99,680	99,680	99,680	99,680

The table presents the regression results for the impact of credit information sharing on bank lending. The credit information sharing is proxied by private credit bureau coverages *PRIV*. The dependent variable is bank lending measured by GLOAN. *GLOAN* is the change of the natural logarithm of total gross loans in current year and previous year; *PRIV* is private credit bureau coverage (% of adult population); *IFRS* and *BDI* are proxies of information environment; *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *BDI* is a business extent of disclosure index; *CR* is a creditor rights index; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *NIM* is a net interest margin; *EFFICIENCY* is a cost-to-income ratio; *DEP* is a ratio of total deposits to total assets; *LLR* is a ratio of loan loss reserves to gross loans; *GDPG* is a growth rate of GDP; *INF* is inflation; *CCT3* is a concentration index calculated from the fraction of assets held by the 3 largest banks in a country: *CAPITAL STR* is a capital stringency index measuring the extent of both initial and overall capital stringency in a country. Further detail of all variables is presented in Table 2-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-

level are applied in all estimations.
* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 2-10: Estimation Results with Alternative Proxy of Credit Information Sharing - Public Credit Registry Coverages

Variable	GLOAN						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PUB	-0.076	-0.043	-0.042	-0.074	-0.062	-0.076	-0.202
	(1.02)	(0.87)	(1.12)	(-1.10)	(-1.27)	(-1.12)	(-0.74)
IFRS		0.104**	0.076*				
		(2.55)	(1.93)				
IFRS * PUB			0.032				
			(1.02)				
BDI				0.012*	0.012		
				(1.86)	(0.89)		
BDI * PUB					-0.04		
					(-0.45)		
CR						0.036**	0.045**
						(2.27)	-2.43
CR * PUB							0.031
							(0.71)
SIZE	0.103***	0.106***	0.107***	0.103***	0.103***	0.103***	0.103***
	(3.74)	(3.69)	(3.66)	(3.71)	(3.70)	(3.74)	(3.74)
NIM	0.478*	0.466*	0.466*	0.478*	0.470*	0.478*	0.478*
	(1.84)	(1.73)	(1.73)	(1.84)	(1.79)	(1.84)	(1.84)
EFFICIENCY	-0.052***	-0.052***	-0.052***	-0.052***	-0.051***	-0.052***	-0.052***
	(-3.30)	(-3.37)	(-3.37)	(-3.31)	(-3.31)	(-3.30)	(-3.30)
DEP	-0.004	-0.008	-0.008	-0.004	-0.005	-0.004	-0.004
	(-0.04)	(-0.08)	(-0.08)	(-0.04)	(-0.05)	(-0.04)	(-0.04)
LLR	-0.029***	-0.029***	-0.029***	-0.029***	-0.029***	-0.029***	-0.029***
	(-2.65)	(-2.65)	(-2.65)	(-2.65)	(-2.65)	(-2.65)	(-2.65)
GDPG	1.582***	1.568***	1.569***	1.580***	1.550***	1.582***	1.576***
	(3.68)	(3.64)	(3.64)	(3.66)	(3.57)	(3.68)	(3.66)
INF	0.066	0.056	0.056	0.066	0.066	0.066	0.066
	(0.27)	(0.23)	(0.23)	(0.27)	(0.27)	(0.27)	(0.26)
CCT3	0.077	0.068	0.066	0.076	0.071	0.077	0.074
	(1.00)	(0.86)	(0.83)	(0.99)	(0.94)	(1.00)	(0.95)
CAPITAL_STR	-0.009*	-0.010*	-0.009*	-0.009*	-0.009*	-0.009*	-0.009*
	(-1.84)	(-1.96)	(-1.93)	(-1.84)	(-1.91)	(-1.84)	(-1.82)
Constant	-0.617**	-0.593**	-0.592**	-0.598**	-0.574**	-0.617**	-0.615**
	(-2.41)	(-2.28)	(-2.29)	(-2.37)	(-2.25)	(-2.41)	(-2.41)
R-squared	0.273	0.273	0.273	0.273	0.273	0.273	0.273
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	99,680	99,680	99,680	99,680	99,680	99,680	99,680

The table presents the regression results for the impact of credit information sharing on bank lending. Credit information sharing is proxied by public credit registry coverages *PUB*. The dependent variable is bank lending measured by GLOAN. *GLOAN* is the change of the natural logarithm of total gross loans in current year and previous year; *PUB* is public credit bureau coverage (% of adult population)*;* *IFRS* and *BDI* are proxies of information environment; *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *BDI* is a business extent of disclosure index; *CR* is a creditor rights index; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *NIM* is a net interest margin; *EFFICIENCY* is a cost-to-income ratio; *DEP* is a ratio of total deposits to total assets; *LLR* is a ratio of loan loss reserves to gross loans; *GDPG* is a growth rate of GDP; *INF* is inflation; *CCT3* is a concentration index calculated from the fraction of assets held by the 3 largest banks in a country: *CAPITAL_STR* is a capital stringency index measuring the extent of both initial and overall capital stringency in a country. Further detail of all variables is presented in Table 2-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.
* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 2-11: Estimation Results with Additional Control Variables

Variable	GLOAN						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DEPTH	0.021*	0.020**	0.025**	0.024*	0.030*	0.021**	0.077
	(1.89)	(2.01)	(2.06)	(1.93)	(1.85)	(2.05)	(1.29)
IFRS		0.09**	0.06*				
		(2.32)	(1.78)				
IFRS * DEPTH			-0.051*				
			(-1.68)				
BDI				0.007**	0.006*		
				(2.24)	-1.91		
BDI * DEPTH					-0.001**		
					(-2.21)		
CR						0.01**	0.045***
						(2.27)	(3.46)
CR * DEPTH							-0.0086***
							(-3.69)
SIZE	0.110***	0.114***	0.114***	0.110***	0.110***	0.110***	0.110***
	(3.52)	(3.51)	(3.51)	(3.50)	(3.49)	(3.52)	(3.52)
NIM	0.504**	0.486*	0.487*	0.504**	0.504**	0.504**	0.505**
	(2.03)	(1.87)	(1.87)	(2.03)	(2.03)	(2.03)	(2.03)
EFFICIENCY	-0.054***	-0.054***	-0.054***	-0.054***	-0.054***	-0.054***	-0.054***
	(-3.71)	(-3.83)	(-3.83)	(-3.72)	(-3.72)	(-3.71)	(-3.75)
DEP	-0.011	-0.018	-0.018	-0.011	-0.011	-0.011	-0.010
	(-0.11)	(-0.18)	(-0.18)	(-0.11)	(-0.11)	(-0.11)	(-0.10)
LLR	-0.029***	-0.029***	-0.029***	-0.029***	-0.029***	-0.029***	-0.029***
	(-2.65)	(-2.66)	(-2.66)	(-2.65)	(-2.65)	(-2.65)	(-2.65)
GDPG	1.574***	1.546***	1.545***	1.574***	1.568***	1.574***	1.558***
	(4.19)	(4.12)	(4.08)	(4.17)	(4.13)	(4.19)	(4.17)
INF	0.093	0.080	0.081	0.093	0.094	0.093	0.135
	(0.39)	(0.34)	(0.34)	(0.39)	(0.39)	(0.39)	(0.56)
CCT3	0.049	0.039	0.040	0.049	0.049	0.049	0.055
	(0.70)	(0.54)	(0.55)	(0.69)	(0.70)	(0.70)	(0.78)
CAPITAL_STR	-0.012**	-0.012**	-0.012**	-0.012**	-0.012**	-0.012**	-0.012**
	(-2.18)	(-2.22)	(-2.21)	(-2.17)	(-2.07)	(-2.18)	(-2.18)
DEPOSIT_INS	0.022*	0.018	0.018	0.023*	0.024	0.022*	0.022
	(1.74)	(0.70)	(0.74)	(1.75)	(0.75)	(1.74)	(0.78)
Constant	-0.424*	-0.406	-0.408	-0.420*	-0.390	-0.424*	-0.502**
	(-1.75)	(-1.65)	(-1.65)	(-1.76)	(-1.53)	(-1.75)	(-2.03)
R-squared	0.274	0.275	0.275	0.274	0.274	0.274	0.274
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	99,680	99,680	99,680	99,680	99,680	99,680	99,680

The table presents the regression results for the impact of credit information sharing on bank lending with additional control variable. The additional control variable is *DEPOSIT_INS*. The dependent variable is bank lending measured by GLOAN. *GLOAN* is the change of the natural logarithm of total gross loans in current year and previous year; *DEPTH* is depth of credit information sharing index; *IFRS* and *BDI* are proxies of information environment; *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *BDI* is a business extent of disclosure index; *CR* is a creditor rights index; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *NIM* is a net interest margin; *EFFICIENCY* is a cost-to-income ratio; *DEP* is a ratio of total deposits to total assets; *LLR* is a ratio of loan loss reserves to gross loans; *GDPG* is a growth rate of GDP; *INF* is inflation; *CCT3* is a concentration index calculated from the fraction of assets held by the 3 largest banks in a country: *CAPITAL_STR* is a capital stringency index measuring the extent of both initial and overall capital stringency in a country; *DEPOSIT_INS* is a dummy for deposit insurance taking a value of one if the country has adopted a deposit insurance regime, and zero otherwise. Further detail of all variables is presented in Table 2-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level

are applied in all estimations.
* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 2-12: Estimation Results with Additional Control Variables (Continued)

Variable	GLOAN						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DEPTH	0.019*	0.020**	0.022*	0.021*	0.035*	0.021**	0.08
	(1.87)	(2.06)	(1.75)	(1.84)	(1.82)	(2.07)	(1.51)
IFRS		0.1**	0.05				
		(2.30)	(1.60)				
IFRS * DEPTH			-0.06*				
			(-1.70)				
BDI				0.007**	0.006*		
				(2.67)	(1.91)		
BDI * DEPTH					-0.003**		
					(-2.32)		
CR						0.03*	0.038***
						(1.91)	(3.43)
CR * DEPTH							-0.007***
							(-3.79)
SIZE	0.108***	0.112***	0.112***	0.109***	0.108***	0.108***	0.108***
	(3.44)	(3.42)	(3.42)	(3.42)	(3.42)	(3.44)	(3.44)
NIM	0.503**	0.485*	0.485*	0.503**	0.503**	0.503**	0.504**
	(2.00)	(1.84)	(1.84)	(2.00)	(2.00)	(2.00)	(2.00)
EFFICIENCY	-0.054***	-0.055***	-0.055***	-0.054***	-0.054***	-0.054***	-0.054***
	(-3.87)	(-4.00)	(-4.00)	(-3.89)	(-3.89)	(-3.87)	(-3.91)
DEP	0.008	0.003	0.003	0.008	0.008	0.008	0.010
	(0.08)	(0.03)	(0.03)	(0.08)	(0.08)	(0.08)	(0.10)
LLR	-0.029***	-0.029***	-0.029***	-0.029***	-0.029***	-0.029***	-0.029***
	(-2.66)	(-2.66)	(-2.66)	(-2.66)	(-2.66)	(-2.66)	(-2.66)
GDPG	1.576***	1.547***	1.545***	1.574***	1.568***	1.576***	1.560***
	(3.95)	(3.87)	(3.84)	(3.91)	(3.88)	(3.95)	(3.93)
INF	0.051	0.034	0.035	0.049	0.050	0.051	0.092
	(0.23)	(0.16)	(0.16)	(0.23)	(0.23)	(0.23)	(0.42)
CCT3	0.062	0.053	0.053	0.062	0.062	0.062	0.068
	(0.89)	(0.73)	(0.74)	(0.88)	(0.88)	(0.89)	(0.97)
CAPITAL_STR	-0.011*	-0.011*	-0.011*	-0.011*	-0.010*	-0.011*	-0.011*
	(-1.89)	(-1.94)	(-1.94)	(-1.89)	(-1.79)	(-1.89)	(-1.89)
POLITIC	0.049***	0.046***	0.046***	0.047***	0.047***	0.049***	0.049***
	(-3.02)	(-2.88)	(-2.87)	(-2.93)	(-2.87)	(-3.02)	(-3.02)
Constant	-0.399	-0.376	-0.379	-0.363	-0.336	-0.399	-0.477*
	(-1.61)	(-1.50)	(-1.50)	(-1.45)	(-1.26)	(-1.61)	(-1.89)
R-squared	0.275	0.276	0.276	0.275	0.275	0.275	0.275
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	99,680	99,680	99,680	99,680	99,680	99,680	99,680

The table presents the regression results for the impact of credit information sharing on bank lending with additional control variable. The additional control variable is *POLITIC*. The dependent variable is bank lending measured by GLOAN. *GLOAN* is the change of the natural logarithm of total gross loans in current year and previous year; *DEPTH* is depth of credit information sharing index; *IFRS* and *BDI* are proxies of information environment; *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *BDI* is a business extent of disclosure index; *CR* is a creditor rights index; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *NIM* is a net interest margin; *EFFICIENCY* is a cost-to-income ratio; *DEP* is a ratio of total deposits to total assets; *LLR* is a ratio of loan loss reserves to gross loans; *GDPG* is a growth rate of GDP; *INF* is inflation; *CCT3* is a concentration index calculated from the fraction of assets held by the 3 largest banks in a country: *CAPITAL_STR* is a capital stringency index measuring the extent of both initial and overall capital stringency in a country; *POLITIC* is a political stability index. Further detail of all variables is presented in Table 2-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

* indicates significance at the 10% level

** indicates significance at the 5% level

*** indicates significance at the 1% level

Table 2-13: Sub-Sample Analysis

Variable	*GLOAN*		*GLOAN*		*GLOAN*	
	IFRS Adoption	NON-IFRS Adoption	HIGH BDI	LOW BDI	HIGH CR	LOW CR
	(1)	(2)	(3)	(4)	(5)	(6)
DEPTH	0.022	0.037*	0.04	0.03**	0.015*	0.041***
	(0.44)	(1.84)	(0.94)	(2.61)	(1.89)	(3.52)
SIZE	0.214***	0.081***	0.078***	0.158***	0.163***	0.070***
	(5.20)	(3.06)	(3.26)	(3.63)	(5.08)	(3.65)
NIM	0.325*	0.775	1.520*	0.268***	0.404***	0.609
	(1.98)	(1.19)	(1.83)	(3.02)	(3.11)	(1.22)
EFFICIENCY	-0.029	-0.062***	-0.077***	-0.013	-0.007	-0.067***
	(-1.61)	(-4.55)	(-17.67)	(-0.69)	(-0.37)	(-8.31)
DEP	0.326***	-0.101	-0.060	0.186**	0.180***	-0.092
	(5.35)	(-1.40)	(-0.57)	(2.59)	(2.80)	(-0.97)
LLR	-0.028***	-0.209**	-0.051***	-0.028***	-0.027***	-0.244***
	(-2.70)	(-2.21)	(-2.78)	(-2.65)	(-2.66)	(-2.67)
GDPG	1.376***	2.033***	1.275**	1.655***	1.742***	1.738***
	(3.46)	(3.96)	(2.59)	(3.51)	(3.65)	(4.27)
INF	0.426	-0.054	0.066	0.223	0.167	0.005
	(0.86)	(-0.35)	(0.29)	(0.78)	(0.59)	(0.04)
CCT3	0.023	0.207*	0.130	0.024	0.101	0.046
	(0.27)	(1.87)	(1.13)	(0.31)	(1.37)	(0.39)
CAPITAL_STR	-0.008	-0.006	-0.018**	-0.003	-0.003	-0.014
	(-1.07)	(-0.58)	(-2.19)	(-0.38)	(-0.56)	(-1.47)
Constant	-1.413***	-0.176	-0.353*	-0.885***	-0.983***	-0.077
	(-4.99)	(-0.88)	(-1.82)	(-3.01)	(-4.38)	(-0.52)
R-squared	0.338	0.27	0.273	0.303	0.304	0.271
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30,324	69,356	70,797	28,883	34,993	64,687

The table presents the regression results of subsample analysis for the impact of credit information sharing on bank lending. The subsamples are classified based on proxies of informational environment and creditor rights index. "IFRS" is the group of observations with IFRS adoption proxied for high transparent information environment, while "NON-IFRS" is the group of observations with NON-IFRS adoption proxied for low transparent information environment. "HIGH BDI" is the group of observations with BDI above the median value of the sample, while "LOW BDI" is the group of observations with BDI below the median value of the sample. "HIGH CR" is the group of observations with CR above the median value of the sample, while "LOW CR" is the group observations with CR below the median value of the sample.

The dependent variable is bank lending measured by GLOAN. *GLOAN* is the change of the natural logarithm of total gross loans in current year and previous year; *DEPTH* is depth of credit information sharing index; *IFRS* and *BDI* are proxies of information environment; *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *BDI* is a business extent of disclosure index; *CR* is a creditor rights index; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *NIM* is a net interest margin; *EFFICIENCY* is a cost-to-income ratio; *DEP* is a ratio of total deposits to total assets; *LLR* is a ratio of loan loss reserves to gross loans; *GDPG* is a growth rate of GDP; *INF* is inflation; *CCT3* is a concentration index calculated from the fraction of assets held by the 3 largest banks in a country: *CAPITAL_STR* is a capital stringency index measuring the extent of both initial and overall capital stringency in a country. Further detail of all variables is presented in Table 2-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 2-14: Non-USA Sample Analysis

Variable	GLOAN						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DEPTH	0.044*	0.043**	0.049**	0.044*	0.047**	0.044*	0.13
	(1.89)	(2.02)	(2.23)	(1.92)	(2.01)	(1.81)	(0.91)
IFRS		0.078*	0.05				
		(1.73)	(0.78)				
IFRS * DEPTH			-0.03*				
			(-1.83)				
BDI				0.0065**	0.008*		
				(2.56)	(1.78)		
BDI * DEPTH					-0.002*		
					(-1.69)		
CR						0.016**	0.05***
						(2.36)	(3.52)
CR * DEPTH							-0.012***
							(-3.68)
SIZE	0.150***	0.157***	0.157***	0.150***	0.150***	0.150***	0.150***
	(5.41)	(6.20)	(6.19)	(5.43)	(5.37)	(5.41)	(5.40)
NIM	0.312***	0.294***	0.295***	0.312***	0.312***	0.312***	0.313***
	(3.24)	(2.63)	(2.63)	(3.24)	(3.23)	(3.24)	(3.24)
EFFICIENCY	-0.016	-0.017	-0.016	-0.016	-0.016	-0.016	-0.016
	(-0.97)	(-1.02)	(-1.02)	(-0.98)	(-0.98)	(-0.97)	(-0.99)
DEP	0.181***	0.178***	0.178***	0.181***	0.181***	0.181***	0.184***
	(3.58)	(3.63)	(3.64)	(3.58)	(3.57)	(3.58)	(3.66)
LLR	-0.029***	-0.029***	-0.029***	-0.029***	-0.029***	-0.029***	-0.029***
	(-2.68)	(-2.68)	(-2.68)	(-2.68)	(-2.68)	(-2.68)	(-2.68)
GDPG	1.562***	1.561***	1.558***	1.557***	1.553***	1.562***	1.536***
	(4.09)	(4.10)	(4.09)	(4.06)	(4.03)	(4.09)	(4.03)
INF	0.175	0.160	0.162	0.174	0.175	0.175	0.221
	(0.73)	(0.67)	(0.68)	(0.73)	(0.74)	(0.73)	(0.92)
CCT3	0.063	0.052	0.054	0.060	0.061	0.063	0.070
	(1.00)	(0.77)	(0.80)	(0.96)	(0.96)	(1.00)	(1.10)
CAPITAL_STR	-0.006	-0.006	-0.006	-0.006	-0.006	-0.006	-0.006
	(-0.95)	(-1.05)	(-1.08)	(-0.95)	(-0.89)	(-0.95)	(-0.95)
Constant	-0.882***	-0.824***	-0.831***	-0.806***	-0.784***	-0.882***	-0.874***
	(-4.80)	(-4.48)	(-4.46)	(-3.97)	(-3.55)	(-4.80)	(-4.85)
R-squared	0.29	0.293	0.293	0.29	0.29	0.29	0.291
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	45,119	45,119	45,119	45,119	45,119	45,119	45,119

The table presents the regression results of subsample analysis for the impact of credit information sharing on bank lending. All regressions exclude banks in the USA. The dependent variable is bank lending measured by GLOAN. *GLOAN* is t the change of the natural logarithm of total gross loans in current year and previous year; *DEPTH* is depth of credit information sharing index; *IFRS* and *BDI* are proxies of information environment; *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *BDI* is a business extent of disclosure index; *CR* is a creditor rights index; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *NIM* is a net interest margin; *EFFICIENCY* is a cost-to-income ratio; *DEP* is a ratio of total deposits to total assets; *LLR* is a ratio of loan loss reserves to gross loans; *GDPG* is a growth rate of GDP; *INF* is inflation; *CCT3* is a concentration index calculated from the fraction of assets held by the 3 largest banks in a country: *CAPITAL_STR* is a capital stringency index measuring the extent of both initial and overall capital stringency in a country. Further detail of all variables is presented in Table 2-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.
* indicates significance at the 10% level

** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 2-15: IV Approach for the Impact of Credit Information Sharing on Bank Lending

Variable	*GLOAN*	
	(1)	(2)
DEPTH	0.116**	
	(2.03)	
SIZE	0.006***	-0.009
	(3.04)	(-0.54)
NIM	0.371***	-0.152
	(3.63)	(-0.31)
EFFICIENCY	-0.072***	-0.011
	(-5.38)	(-0.43)
DEP	-0.043*	0.209
	(-1.80)	(1.42)
LLR	-0.017**	0.005***
	(-2.49)	(4.18)
GDPG	1.630***	-1.398
	(4.71)	(-0.62)
INF	0.243	-5.102***
	(1.59)	(-3.30)
CCT3	-0.058*	-0.583
	(-1.88)	(-1.21)
CAPITAL_STR	-0.003	0.113
	(-0.65)	(1.19)
LEGALORIGIN		2.198***
		(4.53)
ETHNIC_FRAC		-1.710***
		(-4.77)
LATITUDE		-1.682
		(-1.47)
Constant	0.146**	5.456***
	(2.14)	(4.92)
R-squared	0.263	0.468
First Stage F-test	14.88	
Second Stage F-test	95.64	
Hansen J	0.618	
Hansen J P-Value	0.734	
Observations	92,795	92,795

The table presents the regression results for the impact of credit information sharing on bank lending. The estimation method is based on an instrumental variable approach. The instruments are legal origins, ethnic fractionalization, and latitude. The 2nd-stage regressions are reported in the odd columns, while the 1st-stage regressions are reported in the even columns.

The dependent variable is bank lending measured by GLOAN. *GLOAN* is the change of the natural logarithm of total gross loans in current year and previous year; *DEPTH* is depth of credit information sharing index; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *NIM* is a net interest margin; *EFFICIENCY* is a cost-to-income ratio; *DEP* is a ratio of total deposits to total assets; *LLR* is a ratio of loan loss reserves to gross loans; *GDPG* is a growth rate of GDP; *INF* is inflation; *CCT3* is a concentration index calculated from the fraction of assets held by the 3 largest banks in a country: *CAPITAL_STR* is a capital stringency index measuring the extent of both initial and overall capital stringency in a country. *LEGALORIGIN* is dummy variable whose value is equal to one if a country has English legal origin and otherwise zero; *ETHNIC_FRAC* is an ethnic fractionalization which captures the ethnic diversity in a country; *LATITUDE* is a latitude which measures the geographical latitude of a country. Further detail of all variables is presented in Table 2-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

* indicates significance at the 10% level

** indicates significance at the 5% level

*** indicates significance at the 1% level

Table 2-16: IV Approach for the Effect of Information Asymmetry on the Linkage between Credit Information Sharing and Bank Lending

Variable	*GLOAN*							
	IFRS Adoption		NON IFRS Adoption		HIGH BDI		LOW BDI	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DEPTH	0.067		0.046*		0.059		0.042*	
	(1.08)		(1.78)		(0.88)		(1.67)	
SIZE	0.003	-0.018	0.008***	0.028	0.008***	-0.017	0.002	0.008
	(1.61)	(-0.75)	(4.94)	(1.26)	(5.17)	(-0.72)	(0.88)	(0.59)
NIM	0.260***	-0.282	0.485**	-0.406	0.442*	0.617	0.332***	0.051
	(5.63)	(-0.66)	(2.45)	(-0.77)	(1.66)	(0.82)	(5.06)	(0.13)
EFFICIENCY	-0.027	-0.000	-0.091***	-0.005	-0.086***	0.007	-0.032	0.065
	(-1.38)	(-0.01)	(-13.37)	(-0.23)	(-10.92)	(0.32)	(-1.43)	(1.15)
DEP	0.025	0.161	-0.070**	0.159	-0.056***	-0.105	-0.001	-0.177
	(1.13)	(0.83)	(-2.39)	(0.90)	(-2.97)	(-1.00)	(-0.03)	(-0.80)
LLR	-0.016**	0.005***	-0.127*	-0.125	0.008**	0.035	-0.017**	0.001
	(-2.46)	(3.75)	(-1.89)	(-1.42)	(2.38)	(1.50)	(-2.47)	(0.67)
GDPG	1.429***	-5.560	1.556***	-1.716	1.725***	-3.651	1.600***	-1.256
	(3.11)	(-1.28)	(3.90)	(-0.50)	(3.54)	(-1.04)	(3.67)	(-0.43)
INF	0.053	-7.867***	0.145	-2.107	0.278	-5.948*	0.118	-3.987*
	(0.26)	(-3.72)	(0.97)	(-1.31)	(1.37)	(-1.74)	(0.93)	(-1.79)
CCT3	-0.015	0.492	-0.114**	-1.750**	-0.042	0.069	-0.033	-1.516**
	(-0.36)	(0.72)	(-2.22)	(-2.39)	(-0.99)	(0.13)	(-0.88)	(-2.01)
CAPITAL_STR	0.007	-0.091	-0.018**	0.307***	-0.001	0.055	-0.010*	0.080
	(1.20)	(-0.70)	(-2.55)	(3.27)	(-0.12)	(0.51)	(-1.86)	(1.03)
LEGALORIGIN		2.211***		0.232		2.083***		0.058
		(4.03)		(0.32)		(4.22)		(0.10)
ETHNIC_FRAC		-2.558***		-3.004***		-0.434		-2.998***
		(-3.52)		(-4.35)		(-0.80)		(-8.37)
LATITUDE		-1.407		-0.972		-2.795*		1.064
		(-1.07)		(-0.68)		(-1.81)		(1.07)
Constant	0.175*	6.261***	0.236***	5.935***	0.070	6.270***	0.251***	5.896***
	(1.73)	(4.22)	(3.10)	(5.13)	(0.98)	(4.29)	(3.27)	(5.80)
R-squared	0.284	0.509	0.271	0.588	0.257	0.601	0.292	0.601
First Stage F-test	12.76		7.092		15.91		27.75	
Second Stage F-test	250.8		243.7		1818		135.9	
Hansen J	2.561		1.26		0.430		1.398	
Hansen J P-Value	0.228		0.437		0.807		0.491	
Observations	28,098	28,098	64,697	64,697	68,879	68,879	23,916	23,916

The table presents the regression results for the impact of information asymmetry on the relationship between credit information sharing and bank lending. The estimation method is based on an instrumental variable approach. The instruments are legal origins, ethnic fractionalization, and latitude. The subsamples are classified based on proxies of information environment. "IFRS" is the group of observations with IFRS adoption proxied for high transparent information environment, while "NON-IFRS" is the group of observations with NON-IFRS adoption proxied for low transparent information environment. "HIGH BDI" is the group of observations with BDI above the median value of the sample, while "LOW BDI" is the group of observations with BDI below the median value of the sample. The 2nd-stage regressions are reported in the odd columns, while the 1st-stage regressions are reported in the even columns.

The dependent variable is bank lending measured by GLOAN. *GLOAN* is the change of the natural logarithm of total gross loans in current year and previous year; *DEPTH* is depth of credit information sharing index; *IFRS* and *BDI* are proxies of information environment; *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *BDI* is a business extent of disclosure index; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *NIM* is a net interest margin; *EFFICIENCY* is a cost-to-income ratio; *DEP* is a ratio of total deposits to total assets; *LLR* is a ratio of loan loss reserves to gross loans; *GDPG* is a growth rate of GDP; *INF* is inflation; *CCT3* is a concentration index calculated from the fraction of assets held by the 3 largest banks in a country: *CAPITAL_STR* is a capital stringency index measuring the extent of both initial and overall capital stringency in a country. *LEGALORIGIN* is dummy variable whose value is equal to one if a country has English legal origin and otherwise zero; *ETHNIC_FRAC* is an ethnic fractionalization which captures the ethnic diversity in a country; *LATITUDE* is a latitude which measures the geographical latitude of a country. Further detail of all variables is presented in Table 2-1 in this chapter.

Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.
* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 2-17: IV Approach for the Effect of Creditor Rights on the Linkage between Credit Information Sharing and Bank Lending

Variable	*GLOAN*			
	HIGH CR		LOW CR	
	(1)	(2)	(3)	(4)
DEPTH	0.049		0.107*	
	(0.53)		(1.94)	
SIZE	0.007***	0.029	0.009***	-0.031
	(3.10)	(1.56)	(4.57)	(-1.22)
NIM	0.265***	-1.083	0.341*	0.054
	(3.47)	(-1.15)	(1.91)	(0.11)
EFFICIENCY	-0.041*	-0.032	-0.087***	-0.017
	(-1.93)	(-0.38)	(-10.40)	(-0.90)
DEP	0.014	0.306*	-0.021	-0.011
	(0.52)	(1.80)	(-0.66)	(-0.10)
LLR	-0.016**	0.004***	-0.149**	-0.016
	(-2.45)	(3.95)	(-2.35)	(-0.45)
GDPG	1.538***	-0.419	1.692***	-4.443
	(3.44)	(-0.12)	(5.09)	(-1.11)
INF	-0.050	-5.819***	0.117	-4.958
	(-0.33)	(-2.96)	(0.41)	(-1.49)
CCT3	-0.074**	-0.079	0.159*	-1.626
	(-2.08)	(-0.13)	(1.85)	(-1.15)
CAPITAL_STR	-0.003	-0.028	-0.022*	0.218*
	(-0.40)	(-0.26)	(-1.82)	(1.94)
LEGALORIGIN		1.607***		1.436
		(2.83)		(1.15)
ETHNIC_FRAC		-1.712***		-0.751
		(-2.72)		(-0.73)
LATITUDE		-0.092		-4.245**
		(-0.07)		(-2.56)
Constant	0.315***	4.949***	-0.179	7.306***
	(4.08)	(4.00)	(-1.23)	(4.29)
R-squared	0.287	0.443	0.26	0.563
First Stage F-test	10.15		3.016	
Second Stage F-test	112.6		691.9	
Hansen J	2.219		0.813	
Hansen J P-Value	0.271		0.666	
Observations	28,563	28,563	64,232	64,232

The table presents the regression results for the impact of credit rights on the relationship between credit information sharing and bank lending. The estimation method is based on an instrumental variable approach. The instruments are legal origins, ethnic fractionalization, and latitude. The subsamples are classified based on creditor rights index. "HIGH CR" is the group of observations with CR above the median value of the sample, while "LOW CR" is the group observations with CR below the median value of the sample. The 2nd-stage regressions are reported in the odd columns, while the 1st-stage regressions are reported in the even columns.
The dependent variable is bank lending measured by GLOAN. *GLOAN* is the change of the natural logarithm of total gross loans in current year and previous year; *DEPTH* is depth of credit information sharing index; *CR* is a creditor rights index; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *NIM* is a net interest margin; *EFFICIENCY* is a cost-to-income ratio; *DEP* is a ratio of total deposits to total assets; *LLR* is a ratio of loan loss reserves to gross loans; *GDPG* is a growth rate of GDP; *INF* is inflation; *CCT3* is a concentration index calculated from the fraction of assets held by the 3 largest banks in a country: *CAPITAL_STR* is a capital stringency index measuring the extent of both initial and overall capital stringency in a country. *LEGALORIGIN* is dummy variable whose value is equal to one if a country has English legal origin and otherwise zero; *ETHNIC_FRAC* is an ethnic fractionalization which captures the ethnic diversity in a country; *LATITUDE* is a latitude which measures the geographical latitude of a country. Further detail of all variables is presented in Table 2-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.
* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Chapter 3: Credit Information Sharing and Bank Risk: The Role of Information Asymmetry and Bank Competition

3.1 Introduction

The findings in chapter 2 show that credit information sharing promotes bank lending. As credit information sharing facilitates bank lending decision, it may encourage banks to provide more credits to a broader range of borrowers. On the one hand, from a positive perspective, expansion of credits to a broader range of borrowers enhances overall economic growth (Levine 2005). On the other hand, from a more negative perspective, an increase in lending may lead to higher access to credit for riskier borrowers. The disproportionally high entry of risky borrowers may lead to deteriorated bank portfolios with higher default rates. The high entry of risky borrowers could lead to increasing bank risk and probability of banking crises. Although the results in chapter 2 suggest that credit information sharing increases bank lending, bank risk may increase or may decrease. Therefore, in this chapter, we investigate further whether credit information sharing is likely to influence bank risk.

Bank stability is important for the growth of the economy, sustainability and going concern of the financial sector (Levine 1997, 2005; Demirgüç-Kunt & Levine 2009). The adverse consequences of the 2008-2009 financial crisis have brought the renewed attention of the banking stability to increasing number of academics and policymakers. Widespread failures and losses of financial institutions can impose an externality on the rest of the economy, and the global financial crisis of 2007–2009 provides ample evidence of the importance of containing this risk (Acharya *et al.* 2017). Thus, it is necessary to understand the various factors that affect bank risk.

Theoretically, credit information sharing among banks may decrease bank risk. Specifically, credit information sharing reduces adverse selection and moral hazard problems (Pagano & Jappelli 1993), increases borrowers' effort to repay their debts (Padilla & Pagano 1997, 2000), and prevents excessive lending when each borrower may patronize several banks (Bennardo *et al.* 2014). This should translate into lower bank risk. However, the theory also predicts that credit information sharing may lead to looser screening requirements and lower post-lending effort in monitoring (Dell'Ariccia & Marquez 2006), contributing to rapid credit expansion and lending to riskier borrowers. This may lead to an increase in bank risk.

Several recent studies have examined the relationship between credit information sharing and bank risk at country level and bank level. Despite the ambiguous role of credit information sharing on bank risk, empirical studies point to the same direction that credit information sharing is associated with lower bank risk and less likelihood of banking crises (Jappelli & Pagano 2002; Brown *et al.* 2009; Houston *et al.* 2010; Büyükkarabacak & Valev 2012). Furthermore, these findings show that credit information sharing reduces the adverse impact of creditor rights on bank risk (Houston *et al.* 2010) and reduces the adverse effect of credit boom on the likelihood of banking crises (Büyükkarabacak & Valev 2012).

Although recent empirical studies have been drawn to the benefits of credit information sharing on mitigating bank risk, such impact may also be influenced by banking competition. The relationship between credit information sharing and bank risk has never been tested before under different degree of banking competition. Therefore, the second objective of this chapter attempts to examine whether the impact of credit information sharing on bank risk varies under different degree of banking competition.

In competitive banking markets, adverse selection and moral hazard problems are more intense compared to less competitive banking markets (Shaffer 1998; Dell'Ariccia 2001; Marquez 2002). Banks in competitive banking markets have less incentive to screen and monitor borrowers after lending. Failure to adequately screen and monitor leads to riskier portfolios and weaker balance sheets with potentially negative effects on bank stability (Dell'Ariccia & Marquez 2006). With the role of credit information sharing in reducing adverse selection and moral hazard problems (associated with borrowers), its impact on bank risk could be more pronounced in banking markets with a high degree of competition. Thus, there is potential interaction effect between credit information sharing and bank competition on bank risk.

In addition, we study whether the relationship between credit information sharing and bank risk is also influenced by the level of the country information environment. Like the previous chapter, we proxy the transparency of information environment by the mandatory adoption of IFRS and the business extent of disclosure index (BDI). When the information environment becomes more transparent, adverse selection and moral hazard problems are less problematic. Thus, the role of credit information sharing in reducing information problems can be less pronounced in a more transparent information environment.

To perform an empirical investigation, we use a sample of banks around the globe during 2005 to 2013. To examine the association between credit information sharing and bank risk, we follow the study of Houston *et al.* (2010), whose investigation focuses on the effect of creditor rights and credit information sharing on bank risk, the likelihood of a financial crisis and economic growth. However, we complement the study of Houston et al. (2010) in several ways. First, we use a wider range of countries around the globe. While Houston *et al.* (2010) provide an analysis of bank risk in 69 countries, we expand the analysis to banks in 105 countries. Second, we employ cross-country bank-level panel data approach rather than cross-sectional estimation to address the issues. Third, we study the interaction between credit information sharing and banking competition and examine the influence of banking competition on the relationship between credit information sharing and bank risk.

Overall, the results indicate that credit information sharing is negatively associated with bank risk. This finding suggests that bank risk decreases in countries with more credit information sharing. Our results rule out the prediction of increasing bank risk, which may be due to looser screening requirements and lower post-lending effort in monitoring. In addition, our results show that the negative relationship between credit information sharing and bank risk is less pronounced in a more transparent information environment. The adoption of IFRS attenuates the impact of credit information sharing on bank risk. Furthermore, such impact is moderated by the greater business extent of disclosure index. These results suggest that improved transparency of the information environment mitigates the impact of credit information sharing on bank risk. Our findings also reveal that the negative relationship between credit information sharing and bank risk is more pronounced in banking markets with a high degree of competition among banks.

Our study in this chapter contributes to the existing literature on credit information sharing in two ways. First, we complement Houston *et al.* (2010) on examining the relationship between credit information sharing and bank risk; however, we explore a broader coverage of banks in 105 countries with a more recent dataset. We additionally provide a similar result to them regarding the interaction effect between credit information sharing and creditor rights on bank risk.

Second, our research contributes to the economic consequences of credit information sharing. To the best of my knowledge, our study is the first to provide empirical evidence about the influence of banking competition on the benefits of credit information sharing on bank risk. Given the significance and on-going debate on the role of competition in banking, the same level of credit information sharing may have different effects on bank risk depending on the competitiveness of the banks.

To sum up, this chapter attempts to address these following questions, which are graphically displayed in Figure 3-1 and Figure 3-2:

1. How, and to what extent, credit information sharing affect bank risk?
2. How, and to what extent, information asymmetry and banking market competition affect the relationship between credit information sharing and bank risk?

The rest of the chapter proceeds as follows: Section 2 reviews the related literature and outlines hypotheses development. Section 3 explains data and methodology. Section 4 presents the empirical results, the robustness tests, and the additional tests. Section 5 provides the conclusion.

3.2 Literature Review and Hypotheses Development

3.2.1 Credit Information Sharing and Bank Risk

The theoretical literature explains that credit information sharing can reduce adverse selection, moral hazard (associated with borrowers) and hold-up problem as well as raising the discipline on borrowers' debt repayment leading to an increase in bank lending and the reduction of default rate of individual borrowers (Jappelli & Pagano 2002; Djankov *et al.* 2007; Brown *et al.* 2009; Nana 2014). Consequently, bank loan portfolio (or credit risk) is potentially enhanced by credit information sharing.

For a given set of borrowers, we might expect that all else equal, credit information sharing would translate into lower bank risk. Pagano and Jappelli (1993) investigate the role of credit information sharing on reducing adverse selection in credit markets. They build a model where information asymmetries between lenders and borrowers lead to credit rationing. However, banks do not have the same degree of information about all borrowers – some banks are more familiar with one group of borrowers and other banks are more familiar with another group of borrowers. Sharing this information eliminates the information differences across banks, allowing them to make better judgments about lending to all borrowers. The improved information leads to more lending (Jappelli & Pagano 2002; Djankov *et al.* 2007; Nana 2014) and to lower default probabilities (Jappelli & Pagano 2002; Brown *et al.* 2009).

Additionally, Padilla and Pagano (1997) highlight another benefit from credit information sharing. They suggest that information sharing among banks can reduce moral hazard problem associated with borrowers by reducing rents that each bank can extract from superior information that is unknown to outside banks. In their model, banks can develop relationships with borrowers and can accumulate proprietary information about them. Using their advantageous position, banks can extract information rents by charging high interest rates. The high-interest rates reduce entrepreneurs' incentive to exert effort and increase moral hazard by involving in asset substitution, where borrowers use the funds to invest in riskier projects, leading to greater default probability. We know that a fundamental principle of credit risk management for banks is to write covenants into loan contracts that restrict borrowers from engaging in riskier activities; by monitoring borrowers' activities to see whether they are complying with the covenants and by enforcing the covenants if they are not, lenders can reduce or prevent the moral hazard behavior on the part of borrowers. With increased credit information sharing, it reduces the market power of banks to extract information rents, lowers moral hazard of borrowers and potentially reduces default probability.

Furthermore, the benefits of credit information sharing have been addressed by Klein (1992) as well as Padilla and Pagano (2000). In that framework, borrowers are more likely to repay their debts because information about defaults becomes available to all lenders. The threat of higher future interest rates or outright exclusion from credit markets is a strong disciplining device motivating borrowers to pay on time and in full. As a consequence of borrowers' information sharing, the marginal benefit of monitoring necessarily declines implying a lower equilibrium level of monitoring effort by the creditors; however, with lower equilibrium level of monitoring effort but a greater probability of repayment, the overall quality of loan portfolio should be better.

Finally, Bennardo *et al.* (2014) also support the usefulness of credit information sharing. They argue that credit information sharing reduces the risk of over-borrowing as individual lenders can access information on the overall indebtedness of borrowers from all lending sources. This means that borrowers are less likely to over-borrow and end up default. It is obvious that when borrowers are over-indebted, they are unable to pay any amount to any single source of funds.

Summing up, all models support that credit information sharing helps reduce default rate and translate into lower bank risk by lowering adverse selection, moral hazard associated with borrowers, increasing debt repayment and reducing potential over-borrowing. However, it is possible that the credit information may result in higher bank risk. The credit information sharing may induce banks to provide loans to a wider (potentially riskier) set of borrowers. While credit information sharing lowers the default probability of the individual borrower and increase lending, it may also lead to greater access to credit for riskier borrowers. The disproportionally high entry of risky borrowers alters negatively the composition of the pool of borrowers leading to greater default rates on the aggregate level. Jappelli and Pagano (2006) make the same point. This effect will increase the average expected default rate in the bank's portfolio.

Recent theoretical research also shows that credit information sharing might be the cause of a banking crisis on the macro-level. In the model developed by Dell'Ariccia and Marquez (2006), as banks obtain private information about borrowers and information asymmetries across banks decrease, banks loosen their lending standards, leading to an equilibrium with deteriorated bank portfolios, lower profits, and expanded aggregate credit. Thus, the lending boom that is induced by a reduction in information asymmetries leads to a higher probability of a banking crisis. Also, Dell'Ariccia and Marquez (2006) argue that credit information sharing, when imposed by regulation rather than arising endogenously, leads to lower bank profits and greater banking system instability. Contrast to the theoretical model of Dell'Ariccia and Marquez (2006), Doblas-Madrid and Minetti (2013) empirically explore the consequence of lenders' information sharing using unique contract-level data and find that lenders' entry into the credit bureau does not stop the use of guarantees, suggesting that credit information sharing does not loosen lending standards.

Based on a theoretical point of views, it is still not clear-cut whether credit information sharing would increase or decrease bank risk. It may reduce the probability of default of individual borrowers and subsequently the risk of an individual one; however, the risk of the pool of borrowers may or may not be lower with more credit information sharing. Information sharing among banks may lead to a riskier pool of borrowers and loosen lending standard thereby result in higher bank risk and a higher incidence of the banking crisis. Thus, the conclusion cannot be drawn based on theory without empirical work.

Empirical work has provided evidence investigating the impacts of credit information with international and country-specific analyses including both macro-level and micro-level evidence. On bank-level data, several papers use micro-level data from individual countries to examine empirically the effect of credit information sharing. Consistent with the predictions of Pagano and Jappelli (1993), Padilla and Pagano (1997) and Padilla and Pagano (2000), Doblas-Madrid and Minetti (2013) find that credit information sharing reduces the likelihood of contract delinquencies and defaults, especially when firms are informationally opaque. In an experimental study, Brown and Zehnder (2007) show that the introduction of information sharing significantly raises repayment rates in a market where borrowers are mobile and relationship banking is not feasible. Houston *et al.* (2010) employ bank-level data and provide evidence that the existence and the depth of credit information sharing lower bank-risk taking behaviors and the probability of banking crises.

On the aggregate level data, Jappelli and Pagano (2002) show that credit levels are higher and default risk is lower in countries with credit information sharing. Büyükkarabacak and Valev (2012) as well as Houston *et al.* (2010) find that credit information sharing lowers the likelihood of banking crises. Both show that credit information sharing leads to an improved outcome not only on individual borrowers but also on the aggregate level.

Beside bank-level and aggregate-level, there is empirical evidence by exploiting contract-level data to clearly identify the impact of information sharing. Luoto *et al.* (2007) and De Janvry *et al.* (2010) analyze the staggered use of a registry by the branches of a Guatemalan microfinance institution. They find an increase in loan performance, especially for borrowers that are aware of the existence of the registry. Doblas-Madrid and Minetti (2013) focus on the staggered entry of lenders into a credit registry for the US equipment-financing industry. Entry improved repayment for opaque firms but reduced loan size. In a similar vein, Hertzberg *et al.* (2011) show how lowering the reporting threshold of the Argentinian credit registry resulted in less lending to firms with multiple lending relationships due to improved lender coordination. Lastly, Gonzalez and Osorio (2014) explore the impact of erasing negative borrower information from a Columbian credit bureau. Wiping out this information allowed borrowers to attract larger and longer loans from new lenders. However, the quality of these new loans was significantly lower than those of similar borrowers whose credit history had not been reset.

In summary, theory and evidence illustrates that credit information sharing reduces bank risk as a consequence of a reduction in information asymmetries (Pagano 1993; Padilla & Pagano 1997), an increase in the incentives for debt repayment (Klein 1992; Vercammen 1995; Padilla & Pagano 2000), a reduction in over-borrowing (Bennardo *et al.* 2014) and a reduction in default probability of borrowers on an aggregate-level (Houston *et al.* 2010; Büyükkarabacak & Valev 2012). Thus, we hypothesize as follows:

Hypothesis 1: Credit information sharing is expected to reduce bank risk.

3.2.2 Credit Information Sharing, Information Asymmetry and Bank Risk

Asymmetric information between banks and borrowers impedes efficiency in credit allocation leading to market failure and credit ration (Stiglitz & Weiss 1981). When the information environment becomes more transparent, the role of credit information sharing in reducing bank risk should be less prominent. Following Chapter 2, we employ two variables to proxy for the overall country-level information environment. These proxies are the mandatory adoption of International Financial Reporting Standards (IFRS) and the Business Extent of Disclosure index (BDI).

Several studies show that mandatory IFRS adoption improves analysts' information environment by enhancing transparency and by increasing the comparability of the financial reports (e.g. Barth *et al.* (2008b) ; Bae *et al.* (2008)). Cross-border comparison of financial data becomes easy when the single set of accounting standard is applied globally; thereby, decreasing information acquisition costs, increasing competition and efficiency in the markets (Ball 2006). Similar to Chapter 2, we prefer using mandatory IFRS adoption as a proxy for asymmetric information environment. The key challenge for the study of voluntary IFRS adoption is the fact that firms choose whether and when to adopt IFRS reporting. In our study, it is difficult to differentiate between mandatory and voluntary IFRS as we are trying to see the impact of IFRS adoption on the information environment as a whole. A country may allow some firms to conform to IFRS; however, local GAAP is still allowed for others such that it is impossible to observe the effects of IFRS adoption per se.

Besides the information on financial statements, the agency problem involves misbehavior or misuse of funds by entrepreneurs can eventually be harmful to the interests of shareholders and fund providers (Jensen & Meckling 1979). Disclosure of information related to conflict of interest may thus improve the information transparency. Thus, similar to Chapter 2. We employ the business extent of disclosure index (BDI) obtained from the World Bank's Doing Business. This index measures the extent to which investors are protected through disclosure of ownership and financial information (World Bank's Doing Business 2016). The index also gauges the extent of disclosure of firms' transactions that involve conflicts of interests. Higher value shows that more disclosure of ownership and financial information.

Taken together, both the mandatory adoption of IFRS and higher BDI should reduce the information gap between banks and borrowers to the extent that diminishes the impact of credit information sharing on bank risk. Therefore, we expect that the impact of credit information sharing on bank risk is likely to be less pronounced when there exists mandatory IFRS adoption and the business extent of disclosure index is high. Formally, we hypothesize:

Hypothesis 2: The impact of credit information sharing on bank risk is expected to be less pronounced when the information environment is more transparent (as proxied by IFRS adoption and BDI).

3.2.3 Credit Information Sharing, Banking Competition and Bank Risk

Theories and empirical evidence supporting the impact of credit information sharing on bank risk is explained in the previous section. In this section, further argument is put forward to explain how the relationship between credit information sharing and bank risk would differ under different competitive environments in the banking markets. Overall, there is a large theoretical agreement suggesting a stronger impact of credit information sharing on bank risk in a highly competitive banking market. This is due mainly to the prominent roles of banks in the less competitive market (with high market power) in better monitoring and acquiring borrowers' private information.

Because of information asymmetry between banks and their borrowers that engenders adverse selection and moral hazard problem, banks have an incentive to invest in monitoring and acquiring borrowers' private information to screen out borrowers that do not meet satisfactory lending standards (Cetorelli 2001). Failure to adequately perform these functions leads to riskier portfolios and weaker balance sheets, with potentially negative consequences for the stability of credit markets (Dell'Ariccia & Marquez 2006).

Credit information sharing is a mechanism that can help to alleviate the problem of adverse selection and moral hazard in credit markets (Pagano & Jappelli 1993). As a result, asymmetric information should be less of a concern and banks have less incentive to invest in private information acquisition and to build long-term lending relationships with firms based on the soft information.

When it comes to fulfilling the role of monitoring and acquiring borrowers' private information through screening, banks with high market powers (lower competitive pressure) perform better while intense market competition may distort banks' incentive to perform these roles (Thakor & Boot 2008). Thus, the problem of adverse selection and moral hazard should then be more of a concern for banks in the highly competitive banking market. And the role of credit information sharing can be more prominent in that market. In other words, the impact of credit information sharing on bank risk may be more pronounced when the banking market is characterized by high competition.

To begin with, the adverse selection problem can be more severe in the highly competitive banking market. Supported literature focuses on banks' inability to observe the characteristics of borrowers (heterogeneity of borrowers) and the imperfection of screening tools. Several studies show that both borrowers' heterogeneity and the imperfect screening tests are intensified when the market becomes more competitive.

Introducing exogenous credit-worthiness testing model, Broecker (1990) analyzed how the credit market competition affects the screening problem banks face in the choice of granting loans. The model suggests that competition in lending rates tends to reduce the average quality of loans. This is because borrowers that have been rejected at one bank can easily move and apply for loans at other banks so that the pool of funded projects will exhibit lower average quality as the number of banks increases.

The setup in the study of Broecker (1990) is based on the two types of firms applying for loans with fixed size but differ in their ability to repay loans. Banks decide whether to grant loans by using independent and imperfect screening tests in order to reveal the true quality of firms and compete with each other by setting a loan rate. However, due to the imperfection of screening, the mechanism of the competitive market does not function properly leading to negative consequences for banks. On the one hand, increasing loan rates above competitors can increase profit through the usual price effect. On the other hand, it can worsen the quality of firms accepting loans, thus reducing its profit. A firm will indeed accept the least favorable loan interest rate only after being rejected by all other banks setting more favorable rates, but this implies that the firm has a low creditworthiness on average. This is a "winner' curse" type implication of banks who perform the tests. Because of this winner' curse problem, a higher number of banks performing screening tests decreases the average creditworthiness of firms and increases the probability that a bank does not grant any loan.

Similar to Broecker (1990), Riordan (1995) comes to the same conclusion about the negative consequence of increased competition on screening loan application. Auction theory is applied to the bank loan market and demonstrated how more intense market competition may damage overall market performance. Specifically, using the theory of common value auctions, he shows that higher number of competing banks worsens the informativeness of the signal that banks receive on firms' loan quality and makes them more conservative in granting loans. These two results have a harmful impact on social welfare because they reduce the quality of banks' portfolios and lead to the financing of less efficient investment projects.

Further analysis of winner's curse is also studied by Shaffer (1998). Shaffer shows that the average quality of a bank's pool of borrowers declines as the number of competitors in the market increases. The intuition is based on the possibility that banks screening technologies may not accurately report the borrowers' true characteristics. Suppose the screening model used by banks is indeed imperfect, in the sense that with a certain probability entrepreneurs of high quality can be identified as being of low quality, and vice versa. And the model also assumes that a bank cannot distinguish between a new loan applicant and someone who has already been denied credit by another institution. As a result, rejected applicants (either of high or low quality) can continue to apply to other banks; the more banks there are in the market, the higher the likelihood that a low-quality applicant receives credit. This occurrence is known as winner's curse that is a bank that agrees to extend a loan may be winning the right to fund a lemon (Akerlof 1970).

Shaffer (1998) has extended the analysis of winner's curse problems in lending in several directions. In particular, Shaffer has investigated the impact of banks' use of common information filters (like shared databases and uniform screening criteria) on the winner's curse problems in lending and he has characterized the factors affecting the incentives of banks for using such common filters. Further, his analysis addressed not only how the number of lenders affects an individual bank's loan loss rate, but the study also demonstrated reasons for why de novo banks (recent entrants) will be particularly susceptible to adverse selection leading to loan loss rates being higher for these de novo banks. In addition, Shaffer's study reports important empirical evidence regarding the nature and magnitude of his theoretical predictions as well as an outline of the broader macroeconomic implications of his findings.

Increased competition also reduces the incentive of banks to invest in information acquisition and to screen. The relationship between the degree of competition and incentives of banks to screen is analyzed by Gehrig (1998). In a context where banks use imperfect creditworthiness tests to discriminate between good and bad projects, he shows that incentives to screen increase with the profitability of loans. Thus, more intense competition due to the entry of outside banks worsens the quality of banks' portfolios because it reduces the investment that banks make to improve the precision of their screening tests.

In a similar way to Gehrig (1998), Kanniainen and Stenbacka (1998) find that competition between banks will typically undermine the incentives of banks to avoid classification errors as the incentive to acquire information falls. Thus, these investigations identify a tradeoff between the degree of lending competition and the incentives of banks to acquire information, thereby constituting an information-based relationship between market structure and risk taking in lending markets.

Also focusing on the incentive of bank screening, Cao and Shi (2001) argue that, because an increase in the number of banks operating in the market exacerbates the winner s curse, the number of banks active in performing screening and competing in supplying credit would actually fall; as a result, loan rates would be higher and credit quantities smaller than in a market with fewer banks.

Furthermore, Dell'Ariccia (2000) explores another model of bank screening and shows that, as the number of banks increases, the likelihood that banks will actually screen entrepreneurs, as opposed to lending indiscriminately, decreases. This worsens banks' portfolio quality and diminishes their ability to withstand adverse macroeconomic shocks. His argument is based on the observation that entrepreneurs may be averse to being screened. For instance, the screening process may be time-consuming and in the process the firm may miss profit opportunities. Alternatively, an entrepreneur may not want to reveal the true creditworthiness of the project.

The heterogeneity of borrowers, in turn, affect the competitive mechanism; that is, the competitive market mechanism fails to function properly. In the highly competitive market, each individual bank has a small pool of borrowers; therefore, their information about borrowers is so disperse compared to banks in less competitive banking markets (Marquez 2002). As already mentioned, as the degree of competition increases, it lowers the quality/efficiency of banks' screening. Consequently, more low-quality borrowers obtain financing, and banks may have to increase lending rates to compensate for the higher portfolio risk; thereby, leading to an inverse relationship between competition and level of lending rates (Dell'Ariccia 2001; Marquez 2002). The increase in lending rates may also be the best move for banks when the banking market becomes so competitive that the lending relationship between banks and borrowers no longer sustainable (Petersen & Rajan 1995). In the end, the consequence of higher lending rates intensifies the moral hazard problem associated with borrowers (Padilla & Pagano 2000).

Besides the adverse selection problem, multiple studies show that the moral hazard problem associated with borrowers are less serious in the low competitive banking market. This is because banks with more market power have stronger incentives to monitor the projects of borrowers after lending and to establish long-term relationships. They can enjoy comparative advantages associated with the provision of credit monitoring services and they tend to engage in "credit reputation/rating" because making fewer high-quality credit investments can increase the return on individual investments and thereby encourage financial soundness (Boot & Thakor 2000; Fu *et al.* 2014).

One might argue that market power (lower competitive pressure) allows banks to extract information rents by charging high loan interest rates to borrowers. Higher loan rates would distort entrepreneurial incentives toward the undertaking of excessively risky projects resulting in a reduction in the expected return of investment projects (Rajan 1992; Allen & Gale 2004; Berger *et al.* 2009; Allen *et al.* 2011). However, increased market power may induce banks to raise the lending rate but also strengthens the bank's incentives for project-specific monitoring (Caminal & Matutes 2006), though it reduces the total amount of loanable funds (Cetorelli & Peretto 2000; Cetorelli & Peretto 2012).

Although an increase in interbank competition reduces the borrowing cost, which increases borrowers' surplus, it breaks the lending relationship between banks and their customers at the same time. This is because competition imposes constraints on the ability of borrowers and lenders to intertemporally share the surplus from investment projects (Petersen & Rajan 1995). The breakdown of lending relationship gives banks in a competitive market an incentive to compensate the lost by maximizing the value of deposit insurance put option in the current period by appropriately increasing risk (Besanko & Thakor 2004). Also, when the lending relationship is no longer sustainable, banks in a competitive market may be forced to compensate by charging higher interest rates than banks in a monopolistic market and that higher rates exacerbate the moral hazard problem of borrowers (Petersen & Rajan 1995; Dell'Ariccia 2001; Marquez 2002).

So far, the moral hazard problem related to borrowers is mentioned and the problem is intensified in the highly competitive market. There is no concern for banks' incentive to take more or excessive risk in the competitive market. The only focus is on how the competitive mechanism operates in the presence of market failures. However, according to the banking competition & stability literature, the moral hazard problem can also be associated the banks' behavior itself and the problem is intense when the market is highly competitive (Keeley 1990; Allen & Gale 2004; Allen *et al.* 2011). Therefore, the role of credit information sharing may allow limiting bank risk through limiting their excessive risk-taking behavior, which is common in the highly competitive banking market.

Under traditional view, excessive risk-taking is inevitable in high competitive banking market and the banking system becomes fragile and may end up failure (Allen & Gale 2004). This is because banks in high competitive banking market earn less informational rents from their lending relationships with borrowers. As they lose market power to charge a higher interest rate, their profit margin goes down leading to lower charter-value[10]. This makes banks less able to withstand demand- or supply-side shocks and encourages excessive risk-taking i.e. pursuing riskier investment to increase returns (Marcus 1984; Keeley 1990; Demsetz *et al.* 1996) and have less or no incentives to properly screen borrowers (Boot *et al.* 1993; Allen & Gale 2004). This refers to "competition-fragility" literature.

[10] Keeley (1990); Besanko and Thakor (1993), Boot & Greenbaum 1992; Allen & Gale (2000); Hellmann, Murdoch, and Stiglitz (2000), Matutes and Vives (2000), and Repullo (2004), among others.

In the spirit of the competition-fragility literature, borrowers' information sharing among banks can alleviate the riskiness of banks' investment in the competitive market. Additionally, information sharing among banks can ex-ante limit banks' incentives to take on excessive risk on lending, which may be initially found to potentially end up default. Although banks were to involve in excessive risk-taking, information sharing can also discipline borrowers on repaying debts (Klein 1992; Padilla & Pagano 2000) and prevent them from over-borrowing from multiple-lenders (Bennardo *et al.* 2009, 2014). These results in lower bank risk and in turn prevent banks from over-lending and excessive risk-taking at the same time.

As opposed to the competition-fragility literature, both Boyd and De Nicolo (2005) and Martinez-Miera and Repullo (2010) theoretically show that it is not always the case that high competitive banking market leads to bank risk and failure. This refers to "competition-stability" literature. In particular, Boyd and De Nicolo (2005) argue that a reduction in loan rates from greater competition reduces the loans' probability of default because lower rates provide borrowers an incentive to choose safer investments and less likely to default. Furthermore, they argue that banks in the lower competitive market have high market power to charge higher interest rate and exacerbate moral hazard of borrowers. By taking into account the fact that lower rates also reduce the banks' revenues from performing loans, Martinez-Miera and Repullo (2010) additionally argue that the relationship between competition and the risk of failure is U-shape.

However, both studies of Boyd and De Nicolo (2005) and Martinez-Miera and Repullo (2010) may overlook the fact that credit information sharing among banks can provide borrowers an incentive to repay and keep up with a good credit history (Klein 1992; Padilla & Pagano 2000) and subsequently lower default rate (Jappelli & Pagano 2002). Particularly, credit reporting allows borrowers to build a credit history and to use a documented track record of responsible borrowing and repayment as "reputational collateral" to access credit outside of the established lending relationship (Love & Mylenko 2003) and to keep up with a good repayment history (Padilla & Pagano 2000). In addition, banks with market power have more monitoring capacity and are efficient in monitoring their borrowers (Caminal & Matutes 2006).

To sum up, because banks' screening abilities worsen with increasing competition, tougher competition exacerbate adverse selection and moral hazard problem associated with borrowers. Furthermore, competitive market induces moral hazard of banks to undertake excessive risk-taking to maximize profits. Thus, the effect of credit information sharing on bank risk is expected to be more pronounced in more competitive banking environment, compared to the market with the less competitive environment. To answer the second research question, the related hypothesis is as follows:

Hypothesis 3: The impact of credit information sharing is expected to be more pronounced in the high competitive banking market.

3.3 Data and Methodology

3.3.1 Data

3.3.1.1 Data Source and Sample

Our sample covers 15,558 banks in 105 countries during the period 2005 – 2013. Similar to the previous chapter, we gather data from many different sources and mainly rely on *Bankscope Database* for bank-level accounting information. Other data are taken from the *World Bank's Doing Business Database,* the *IFRS Foundation website*, *Deloitte*, *Simon Fraser University in Canada*, the *World Bank's World Development Indicators (WDI) Database*, the *World Bank's World Governance Indicators (WGI)*, the *World Bank's Bank Regulation & Supervision Survey Database,* the *Deposit Insurance Database*, the *Central Intelligence Agency (CIA)* and the dataset from *LaPorta et al. (1998), La Porta et al. (1999), Easterly (2001) and Djankov et al. (2007).*

In addition to the previous chapter, we collect data on banking competition from the *World Bank's Global Financial Development Database (GFDD)*. These data consist of the Lerner index, the three-largest bank asset concentration ratio, and the five-largest bank asset concentration ratio. Further descriptions and links to data sources can be found in Appendix A.

3.3.1.2 Variable Measurement

3.3.1.2.1 Dependent Variable

A comprehensive literature survey suggests that most of the bank risk indicators can be classified into two broad categories, consisting of accounting-based and market-based indicators. The first and traditional approach to assess the risk of a firm is an accounting-based measure. It is based on the pure accounting information from balance sheet data (see Altman (1968); Altman and Katz (1976); Kaplan and Urwitz (1979); Ohlson (1980); Zmijewski (1984) among others). Key accounting ratios are identified and firm's default probability is estimated by using multivariate discriminant or multinomial choice models. However, the consensus on the accuracy and stress prediction ability of these indicators are relatively low (Singh *et al.* 2015).

These models have generally been criticized on three grounds: (1) the absence of an underlying theoretical model; (2) the timeliness of the information[11]; and (3) the lack of uncertainty and forward-looking component. The selected methodologies also introduce sample selection bias, generating inconsistent coefficient estimates (e.g., Shumway (2001); Chava and Jarrow (2004); Aggarwal *et al.* (2012)). In addition, conservatism and historical cost accounting mean that the true asset values may be very different from the recorded book values. Accounting numbers are subject to manipulation by management. Furthermore, Hillegeist *et al.* (2004) argue that since the accounting statements are prepared on a going-concern basis, they are, by design, of limited utility in predicting bankruptcy. Since the ratios and their weightings are derived from sample analysis, such models are likely to be sample specific (Agarwal & Taffler 2008).

Although the accounting-ratio-based approach is criticized for its lack of theoretical grounding, timeliness of information and lack of forward-looking component, it has 3 things in its favors as stated by Agarwal and Taffler (2008). First, corporate failure is generally not a sudden event. It is rare that firms with good profitability and strong balance sheets file for bankruptcy because of a sudden change in the economic environment. Usually, corporate

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[11] These models base on past performance and information from a firm's financial statement, which available only on quarterly and annually basis; thus, they fail to capture changes in the financial conditions of the borrowing firm and may or may not predict the future.

failure is the culmination of several years of adverse performance and, hence, will be largely captured by the firm's accounting statements. Second, the double entry system of accounting ensures that window dressing the accounts or change in accounting policies will have minimal effect on a measure that combines different facets of accounting information simultaneously. Third, loan covenants are generally based on accounting numbers and this information is more likely to be reflected in accounting-ratio-based models.

As opposed to the accounting ratio-based approach, the second approach is purely market-based. These are indices determined directly in the marketplace (e.g. stock prices, aggregate realized volatility, aggregate market leverage, turbulence (a measure of excess volatility relative to the market), liquidity ratios and credit condition (e.g., credit default swaps)). Similar to the traditional purely balance-sheet-based, most of these measures lack an underlying theoretical framework; however, the timely availability and continuous incorporation of information are prompt and help to improve the relative performance and predictive ability in some cases (see Vassalou and Xing (2004); Jorion (2005); Gropp *et al.* (2006); Agarwal and Taffler (2008); Campbell *et al.* (2011)). According to Fu *et al.* (2014), in the efficient markets, stock prices reflect all available information. Market variables are unlikely to be influenced by firm accounting policies.

The combination of the pure accounting and market-based measures is the contingent claims based model (CCA) of Merton (1974) which provides a theoretical underpinning and answers some of these criticisms. The basic model is based on the priority structure of balance sheet liabilities and uses the standard Black–Scholes option pricing formula to value the junior claims as a call option on firms' value with the value of senior claims as default barrier (Singh *et al.* 2015). The structural underpinning and the combination of market-based and accounting information help obtain a comprehensive set of financial risk indicators, e.g. Distance-to-Default (DtD), probabilities of default, credit spreads, etc.

Moreover, CCA captures the current period instability (using volatility), a forward-looking component (using stock prices) and balance sheet mismatch (using capital structure). It has been widely applied to assess the ability of corporates, banks, and sovereigns to service their debt. Applications to the banking industries follow CCA by interpreting a bank's equity as a call option on its value given the limited liability of shareholders. This approach was further refined by Vasicek (1984) and Crosbie and Bohn (2003) and is applied professionally in Moody's KMV to predict default probability.

Among market-based measures, the DtD approach of Merton has been widely cited and reviewed by the International Monetary Fund (IMF), European Central Bank (ECB) and Office of Federal Research (OFR) as a tool for enhancing bank risk analysis. The DtD has gained prominence, partly due to its successful commercial implementation by Moody's KMV. Several studies have examined the usefulness of DtD as a tool for predicting corporate and bank failure (Kealhofer 2003; Oderda *et al.* 2003; Vassalou & Xing 2004; Gropp *et al.* 2006; Koutsomanoli-Filippaki & Mamatzakis 2009; Harada & Ito 2011; Aggarwal *et al.* 2012; Qi *et al.* 2014; Jessen & Lando 2015). They have found DtD to be a powerful measure to predict bankruptcy and rating downgrades. Comparative analysis of DtD also suggests that DtD can be a powerful proxy to determine default (Hillegeist *et al.* 2004; Vassalou & Xing 2004; Agarwal & Taffler 2008; Bharath & Shumway 2008; Campbell *et al.* 2008; Jessen & Lando 2015). Further information about the DtD model can be found in the appendix.

Beside its supportive comments, there are many criticisms about the Merton model. Because it is a structural model, it requires a number of assumptions. According to Saunders and Allen (2002), the underlying theoretical model requires the assumption of normality of stock returns. Furthermore, Hillegeist *et al.* (2004) suggest two fundamental problems with operationalizing Merton (1974) contingent claims approach: (1) Misspecification due to the restrictive assumptions of the model (e.g. single class of zero coupon debt, all liabilities mature in one-year[12], costless bankruptcy, no safety covenants, default triggered only at maturity, etc.); (2) Measurement errors (e.g. value and volatility of assets are unobservable).

In this study, an accounting-based measure will be estimated for each bank because Z-Score index is widely used in the recent banking literature in measuring bank risk and stability (Boyd & Runkle 1993; Berger *et al.* 2009; Laeven & Levine 2009; Fu *et al.* 2014) and the estimation of the Z-Score index is based on an accounting basis. Also, to calculate a market-based measure of risk, many observations in the sample may be excluded because

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[12] There is no distinction between different types of debts and assume that the firm only has a single zero coupon loan.

most banks in the sample are not listed. Therefore, our primary measure of bank risk is the Z-Score index. The Z-Score is an inverse of a bank's probability of insolvency. A bank becomes insolvent when its asset value drops below its debt. Intuitively, the Z-Score index shows the number of standard deviations below the mean by which profits would have to fall so as to just deplete equity capital (Boyd 2006; Houston *et al.* 2010; Fu *et al.* 2014). In a simple word, Z-Score indicates the number of standard deviations in return on assets that a bank is away from insolvency and thus the likelihood of failure. This measure links to individual bank distress in term of proximity to bankruptcy or entry into bankruptcy. Particularly, this risk measure is monotonically associated with the probability of a bank's default. A higher index shows that a bank is more stable and has a less overall risk.

The calculation of Z-score combines profitability, leverage and the volatility of return into a single ratio as follows:

$$Z_{it} = \frac{ROA_{it} + \frac{E_{it}}{TA_{it}}}{\sigma ROA_{it}} \tag{3-1}$$

where ROA is the return on assets, $\frac{E}{TA}$ is the ratio of equity to total assets, and σROA is the standard deviation (SD) of return on assets. Higher profitability (ROA) and the capitalization levels ($\frac{E}{TA}$) raise the Z-Score index whereas the uncertainty of profitability (σROA) lowers the Z-Score index. Following Agoraki *et al.* (2011) and Soedarmono *et al.* (2013), we use the data of ROA in the current year (t) and the two previous years (t-1 and t-2) to calculate the standard deviation of ROA at time t (three-period rolling window) in Equation (3-1). Due to the high skewness of the Z-Score index, we smooth out by taking a natural logarithm (Laeven & Levine 2009; Houston *et al.* 2010; Dong *et al.* 2014).

For robustness check, we also include another indicator of bank risk, which is a ratio of non-performing loans to total loans (*NPL*). Non-performing loans potentially cause losses for banks (Berger *et al.* 2009; Delis & Kouretas 2011). While the Z-score index measures the overall bank-risk and likelihood of failure, the ratio of non-performing loans to total loans measures the quality of the loan portfolio reflecting the credit risk position of a bank. A higher ratio indicates riskier loan portfolio (or higher credit risk). Furthermore, we modify our calculation of Z-Score according to Agoraki *et al.* (2011) and Soedarmono *et al.* (2013). Instead of using the data of ROA in the current year and two previous years, we use ROA in the current year and three previous years (four-period rolling window: t, t-1, t-2 and t-3) to calculate the standard deviation of ROA at time t. We then use newly calculated standard deviation of ROA to compute Z-Score and obtain the first modified Z-Score, *Z_SCORE_4WIN*. Similarly, data of ROA in the current year and four previous years (five-period rolling window: t, t-1, t-2, t-3 and t-4) are also used for calculating the standard deviation of ROA at time t. We then use newly calculated standard deviation of ROA to compute Z-Score and obtain the second modified Z-Score, *Z_SCORE_5WIN*.

3.3.1.2.2 Explanatory Variables

Credit Information Sharing

Like the previous chapter, we take data on the depth of credit information sharing index (*DEPTH*) from the World Bank's Doing Business database. This index measures rules affecting the scope, accessibility, and quality of credit information available through information-sharing institutions. The value of the index ranges from 0 to 6. The higher the value the better the scope, accessibility, and quality of credit information available from either private credit bureau or public credit registry. Further detail of the depth of credit information sharing index can be found in Table 3-1.

Information Environment Proxy

Like the previous chapter, we proxy the transparency of information environment by the mandatory IFRS adoption and the Business Extent of Disclosure Index (BDI). Data on IFRS adoption is taken from the IFRS Foundation website, Deloitte and Simon Fraser University in Canada. We create a dummy variable for IFRS adoption whose value is equal to one if a country (and year) mandatorily adopt IFRS and zero otherwise. The list of countries with mandatory IFRS adoption is in Appendix B. Data on BDI is taken from the World Bank's Doing Business database. IFRS dummy with a value of one and higher value of BDI are associated with more transparent information environment. More detail of the components of BDI can be found in Appendix C.

Banking Competition

In the studies of banking competition, various instruments are used to measure competition (or market power). There are two possible classifications of the instruments used in the existing literature, a structural and non-structural approach. With regard to a structural approach, it consists of measurements that are not based on any model of industrial organization, such as the so-called structure-conduct-performance paradigm vs efficient structure hypothesis (Berger 1995) as well as the use of market concentration (e.g., Cetorelli and Strahan (2006)). Earlier studies use a structural approach such as concentration-based measures as a proxy for bank competition.

However, there is a growing consensus that concentration measures are not good proxies for bank competition (Berger *et al.* 2004; Claessens & Laeven 2004; Beck *et al.* 2006a). The measures of banking concentration, like Herfindahl Hirschman Index (HHI) and N-bank concentration ratio[13], have also been considered to be ambiguous indicators of market power/competition because they ignore the relationship between revenue and market contestability at the bank-level (Beck *et al.* 2006a; Berger *et al.* 2009; Skully & Perera 2012). Specifically, these measures of concentration do not take into account the competitive behavior of banks in a way that banks with different ownership behave differently and that banks might not compete directly with each other in the same line of business (Beck 2008).

Furthermore, the concentration measures are computed at a nationwide level which may not always coincide with the market power exercised at the local level (Berger *et al.* 2009). Some banking products are competed on an international basis, while other products more often compete on a local basis (Maudos & Solís 2009). Also suggested by Alegria and Schaeck (2008), the measures of concentration can be influenced and sensitive to the differences in the number of banks and so the choice can affect the inferences regarding the degree of competition (Skully & Perera 2012). Furthermore, concentration in banking market can affect bank stability through other channels other than competition (Berger *et al.* 2004; Beck *et al.* 2006a; Beck 2008). Berger *et al.* (2004), Beck *et al.* (2006a), and Beck (2008), to some extent, confirm that concentration measures may not be a good measure of competition. The model of Marquez (2002) also points to the same conclusion that the number of banks may not be a good indicator for measuring market competitiveness.

Also, noted that it is more favorable to use bank-level markup (Lerner index) instead

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[13] N-bank is the number of banks. Three-banks and five-banks are commonly used in computation.

of a concentration ratio (three/five-asset concentration ratios) to measure market power to prevent our empirical analysis from capturing any misleading relationship between banking risk and competition. It may be the case that as bank failures increase, the resulting higher degree of concentration in the industry does not necessarily imply more market power for surviving banks (Beck *et al.* 2006a; Agoraki *et al.* 2011). Banks that do not fail are usually the more efficient bank, which effectively has lower costs in producing the same output (Beck *et al.* 2006a).

Regarding a non-structural approach, it includes diverse instruments based on the industrial organization economics (the so-called "new empirical industrial organization (NEIO)" literature. This literature has been developed primarily from the models of Iwata (1974), Bresnahan (1982), and Panzar and Rosse (1987). More specifically, the published studies use optimization models from which are derived indicators of competition such as the price-cost margin (Lerner index) (e.g. Beighley and McCall (1975); De Guevara and Maudos* (2004); Maudos and De Guevara (2004); Fernandez de Guevara *et al.* (2005)). Some measures competition by employing the Breshnahan mark-up test (e.g. Shaffer (1993); Shaffer and DiSalvo (1994); Suominen (1994)). Moreover, some uses measures of competition such as the Panzar and Rosse test (H-Statistic) (e.g. Molyneux *et al.* (1994); De Bandt and Davis (2000); Bikker and Haaf (2002); Claessens and Laeven (2004); Shaffer (2004b)); the conduct parameter (e.g. Barros (1999); Neven and Röller (1999); De Pinho (2000); Kim and Vale (2001); Canhoto (2004); Coccorese (2005)) Tobin´s q (Keeley 1990) and the Boone indicator (e.g. Boone *et al.* (2004); Boone and Van Leuvensteijn (2010)).

The recent literature favors a non-structural approach such as the H-statistic, the Lerner index and the profit elasticity rather than a structural approach. Claessens and Laeven (2004) and Schaeck *et al.* (2009) derive country-specific Panzar and Rosse (1987) H-statistics, which they subsequently regress on a number of explanatory variables using cross-sectional estimation methods. H-Statistic measures the reaction of output to input prices gauging the competitive behavior of banks. However, it imposes certain restrictive assumptions on banks' cost function. Specifically, under perfect competition, increases in input prices cause total revenue and marginal cost to move together, while in imperfect competition they do not (Beck 2008).

Although the H-statistic of Panzar and Rosse (1987) is used routinely in the banking literature to assess the degree of competition, it has numerous disadvantages. First, the H-statistic maps the various degrees of market power only weakly and, therefore, cannot be viewed as a continuous variable (Maudos & Nagore 2005; Clerides *et al.* 2013). Secondly, although the H-Statistic method of Panzar and Rosse (1987) utilize bank-level data to measure bank market power, the implementation of it requires banking markets to be in the long-run equilibrium, which is unlikely in practice (Bikker & Haaf 2002; Shaffer 2004a; Berger *et al.* 2009). Some authors (see e.g. Shaffer (2004a) among others) convincingly suggest that the H-statistic does not map into a range of oligopoly solution concepts as robustly as the Lerner index does, mainly owing to partial failure to incorporate long-run structural adjustments. Also argued by Bikker *et al.* (2012), H-statistic can actually be used to test the only hypothesis relating to whether the bank operates in long-run equilibrium.

Among the instruments with solid theoretical foundations, the Lerner index takes the lead in measuring competition. The main reasons for its popularity are its simplicity, its straightforward interpretation, and application to empirical studies and the fact that it does not pose stringent data requirements (Clerides *et al.* 2015). Many proponent of using the Lerner Index claims that: firstly, the Lerner index can be estimated for each bank in the sample so that its computation is based on information at bank-level observations (bank-specific variables) for each country and this overcome small sample bias problem (Jeon *et al.* 2011); secondly, the evolution of market power can be analyzed by estimating a Lerner index for each year (Maudos & Nagore 2005); thirdly, it is suitable for examining the market power for banks in different ownership types, sizes and specialization (Claessens & Laeven 2004; Brissimis & Delis 2011; Skully & Perera 2012); and finally, the Lerner Index incorporates both market concentration and demand elasticity so that it is preferable to the market concentration measures per se (Maudos & de Guevara 2007).

Due to favorable arguments, the estimation of the Lerner index has been widely used in the banking sector as an indicator of degrees of competition. Some of the most important studies in this area are Shaffer (1993) for Canadian banks, Angelini and Cetorelli (2003) for Italian banks, Maudos and Pérez (2003) for the Spanish banking sector, and Fernandez de Guevara *et al.* (2005), Maudos and De Guevara (2004) and De Guevara and Maudos* (2004) for a sample of countries of the European Union.

The estimation of Lerner Index shows the ability of an individual bank to charge a price above marginal cost. The divergence between product price and the marginal cost of production is the essence of gauging monopoly power (Maudos & de Guevara 2007; Skully & Perera 2012; Clerides *et al.* 2015). Generally, it is defined as follows:

$$Lerner_{it} = \frac{P_{TA_{it}} - MC_{TA_{it}}}{P_{TA_{it}}} \tag{3-2}$$

Where $P_{TA_{it}}$ is the output price of total assets proxied by the ratio of total revenues (interest and non-interest income) to total assets for bank i at time t and $MC_{TA_{it}}$ is the marginal cost of total assets for bank i at time t.

Given that data on the output price is available but not the marginal cost, an important procedure is to estimate the marginal cost so that Equation (3-2) can be estimated. $MC_{TA_{it}}$ is calculated by taking the derivative from the transcendental logarithmic (translog) cost function as shown below:

$$\begin{aligned} ln\,TC_{it} = {} & \alpha_0 + \beta_1\, ln\,TA_{it} + \frac{1}{2}\beta_2 (ln\,TA_{it})^2 + \frac{1}{2}\sum_{j=1}^{3} \beta_{2j}\, ln\,TA_{it}\, ln\,W_{it}^{j} \\ & + \sum_{j=1}^{3} \alpha_j\, ln\,W_{it}^{j} + \frac{1}{2}\sum_{j=1}^{3}\sum_{k=1}^{3} \alpha_{jk}\, ln\,W_{it}^{j}\, ln\,W_{it}^{k} + \gamma_{1t} T + \frac{1}{2}\gamma_{2t} T^2 \\ & + \gamma_{3t} T\, ln\,TA_{it} + \sum_{j=1}^{3} \gamma_{4t} T\, ln\,W_{it}^{j} + \varepsilon_{it} \end{aligned} \tag{3-3}$$

Simply,

$$
\begin{aligned}
ln\,TC_{it} = {} & \alpha_0 + \beta_1\, ln\,TA_{it} + \frac{1}{2}\beta_2(ln\,TA_{it})^2 + \frac{1}{2}\beta_{21}\, ln\,TA_{it}\, ln\,W_{it}^1 \\
& + \frac{1}{2}\beta_{22}\, ln\,TA_{it}\, ln\,W_{it}^2 + \frac{1}{2}\beta_{23}\, ln\,TA_{it}\, ln\,W_{it}^3 + \alpha_1\, ln\,W_{it}^1 \\
& + \alpha_2\, ln\,W_{it}^2 + \alpha_3\, ln\,W_{it}^3 + \frac{1}{2}\alpha_{11}(ln\,W_{it}^1)^2 + \frac{1}{2}\alpha_{12}\, ln\,W_{it}^1\, ln\,W_{it}^2 \\
& + \frac{1}{2}\alpha_{13}\, ln\,W_{it}^1\, ln\,W_{it}^3 + \frac{1}{2}\alpha_{22}(ln\,W_{it}^2)^2 + \frac{1}{2}\alpha_{21}\, ln\,W_{it}^2\, ln\,W_{it}^1 \\
& + \frac{1}{2}\alpha_{23}\, ln\,W_{it}^2\, ln\,W_{it}^3 + \frac{1}{2}\alpha_{33}(ln\,W_{it}^3)^2 + \frac{1}{2}\alpha_{31}\, ln\,W_{it}^3\, ln\,W_{it}^1 \\
& + \frac{1}{2}\alpha_{32}\, ln\,W_{it}^3\, ln\,W_{it}^2 + \gamma_{1t}T + \frac{1}{2}\gamma_{2t}T^2 + \gamma_{3t}T\, ln\,TA_{it} \\
& + \sum_{j=1}^{3}\gamma_{4t}T\, ln\,W_{it}^j + \varepsilon_{it}
\end{aligned}
\tag{3-4}
$$

Where i denotes banks and t denotes years. TC is total cost consisting of total operating cost plus financial costs. TA is the bank output proxied by total assets. W_1 is the bank's input price of deposits (funds) proxied by the ratio of interest expenses to total deposits and money market funding. W_2 is the bank's input price of labor proxied by the ratio of personal expenses to total assets. W_3 is the bank's input price of physical capital (fixed capital) proxied by the ratio of other operating and administrative expenses to total assets. Time trend is also included to capture the impact of technological changes that could lead to movements in the cost function over time (Maudos & Nagore 2005; Berger *et al.* 2009; Demirgüç-Kunt & Martínez Pería 2010; Skully & Perera 2012; Fu *et al.* 2014). The restriction of symmetry is applied to the estimation such that $\alpha_{jk} = \alpha_{kj}$ (Berger *et al.* 2009; Demirgüç-Kunt & Martínez Pería 2010; Fu *et al.* 2014). In addition, total cost and input price terms are normalized by W_2 to impose linear homogeneity to make sure that there is no change in the cost-minimizing bundle if all of the input prices are multiplied by the same positive scalar (Fu *et al.* 2014). Thus, the allocation of inputs is only affected by the changes in the ratios of the input prices. Marginal cost ($MC_{TA_{it}}$) is then derived as follows:

$$
MC_{TA_{it}} = {}^{\partial TC_{it}}/_{\partial TA_{it}} = \frac{TC_{it}}{TA_{it}}\left[\beta_1 + \beta_2\, ln\,TA_{it} + \sum_{j=1}^{3}\beta_{2j}\, ln\,W_{it}^j + \gamma_{4t}T\right] \tag{3-5}
$$

The symbols in Equation (3-5) remain as defined in Equation (3-3). The Lerner index can be estimated once the marginal cost is obtained from estimating Equation (3-5). Generally, the Lerner Index ranges from zero to one. When the Lerner Index is zero, it corresponds to perfect competition and the larger the values of the Lerner Index the less the competition (greater market power)[14].

For the ease of interpretation, we transform it to a competition measure by subtracting it from one as shown below. Because of the transformation, the higher index is corresponding to higher competition.

$$Competition01_{it} = 1 - Lerner_{it} = 1 - \left[\frac{P_{TA_{it}} - MC_{TA_{it}}}{P_{TA_{it}}}\right] \tag{3-6}$$

For robustness tests, we also employ two other variables which are traditionally used as alternative measures of the degree of competition. Those two variables are three-largest bank asset concentration ratio and five-largest bank asset concentration ratio. They are commonly used in the literature for a period time as a standard measure of market power until they are criticized for their inappropriateness of measuring a degree of competition in the banking sector.

The three-largest bank asset concentration is computed based on the top 3 largest assets of a country's banking system, whereas the five-largest bank-asset concentration ratio is computed differently based on the top 5 largest assets of a country's banking system. Noted that the sample of banks covered by Bankscope changes over the sample period so measured changes in concentration may reflect changes in coverage, not changes in actual concentration (Beck *et al.* 2006a). Thus, as suggest by Beck *et al.* (2006a), including banks beyond the top three might introduce measurement bias given that our sample size changes over the sample period. For this reason, the Herfindahl index of concentration (HHI), which is the sum of the squared market shares of assets in the banking system, is not accurate as it tends to involve measurement bias. Therefore, we favor the three-largest bank asset concentration ratio and the five-largest bank asset concentration ratio. For the ease of

[14] The negative Lerner index implies that pricing is below the marginal cost and could result, for example, from non-optimal bank behavior. However, our sample does not contain any negative Lerner index.

interpretation, we convert the concentration index into a measure of competition by the calculation as shown below:

$$Competition02_{it} = 1 - [3\ Largest\ Banking\ Asset\ Concentration]_{it} \tag{3-7}$$

$$Competition03_{it} = 1 - [5\ Largest\ Banking\ Asset\ Concentration]_{it} \tag{3-8}$$

3.3.1.2.3 Control Variables

Several bank-specific and country-specific variables are controlled and explained in this section. Regarding bank-specific control variables, *SIZE* is a natural logarithm of a bank's total asset, which proxy for a bank's size. Large banks could be less risky due to their greater ability to diversify risk across product lines (Berger *et al.* 2009; Laeven & Levine 2009; Houston *et al.* 2010; Agoraki *et al.* 2011; Delis & Kouretas 2011; Dong *et al.* 2014). To capture the non-linear relationship between bank size and bank risk (Houston *et al.* 2010), we include *SIZE_SQR*, which is the square of a bank's asset. However, large and important banks could be riskier due to the implicit assumption that they are "too-big-to-fail" (Brown & Dinç 2011; Bertay *et al.* 2013; Demirgüç-Kunt & Huizinga 2013). Thus, *TBTF* is included and it is a dummy variable that indicates too-big-too-fail and takes a value of one if the bank's share in the country's total deposits exceeds 10%. *LOAN* is a ratio of net loans to total deposits. It assesses the extent to which customer loans are financed by customer deposits and is related to the bank's liquidity (Dong *et al.* 2014). *EFFICIENCY* is a ratio of cost-to-income. The cost-to-income ratio, defined as the ratio of non-interest operating cost to total bank revenues[15], reflects operations both on and off the balance sheet and the extent to which operating expenses absorb operating revenues. It is used to control for differences in technical efficiency (Agoraki *et al.* 2011) and it is expected to be negatively related to a bank's risk because less efficient banks are likely to take on greater risk to generate profits (Boyd 2006; Agoraki *et al.* 2011; Dong *et al.* 2014).

Regarding country-specific control variables, we include *GDPG*, which is the rate of GDP growth as a proxy for the fluctuations in economic activities. In addition, *INF* is inflation. We also include *CR*, which is a creditor rights index, to control for the level of

[15] Source: http://www.bvd.co.uk/bankscope/bankscope.pdf

creditor rights in a country. In an environment with stronger creditor rights, lenders are more likely to grab collateral, force repayment, or even gain control of the debtor that is in financial distress (Houston *et al.* 2010; Acharya *et al.* 2011). It follows that stronger creditor rights would lead to higher recovery rates in the event of default, which reduces the bank's risk. However, as argued further by Houston *et al.* (2010), with greater protection in the event of a default, a bank may be more willing to lend to riskier borrowers with poorer credit ratings. This effect will increase the average expected default rate in the bank's portfolio. If the higher expected recovery rates in default fail to offset the higher expected default rates, stronger creditor rights would be associated with increased bank risk (Houston *et al.* 2010). Thus, the sign of the correlation between creditor rights and bank risk is ambiguous.

Numerous research points to the same direction that the structure of national bank regulations crucially influences bank risk (Agoraki *et al.* 2011; Barth *et al.* 2013a; Barth *et al.* 2013b). Thus, we include bank regulatory variables to control for the potential impacts of bank regulation on bank risk. Those bank regulatory variables consist of *DEPOSIT_INS, CAPITAL_STR* and *ASSET_DIV*. First, *DEPOSIT_INS* is a dummy variable that takes a value of one if a country has explicit deposit insurance and a value of zero otherwise. As pointed out by Barth *et al.* (2006), deposit insurance intensifies the moral hazard problem in banking because depositors no longer face the risk of losing their savings, which diminishes their incentives and efforts at monitoring bank activities (Houston *et al.* 2010).

Second, we construct *CAPITAL_STR* and *ASSET_DIV* by following Houston *et al.* (2010) and Agoraki *et al.* (2011). *CAPITAL_STR* is an index measuring the extent of both initial and overall capital stringency. It is constructed from several variables that indicate whether the capital requirement reflects certain risk elements (Houston *et al.* 2010). It takes into account whether the minimum capital-asset ratio requirement is in line with the Basel Committee on Banking Supervision guidelines; whether the minimum ratio varies as a function of an individual bank's credit risk and market risk; whether the following items are deducted from the book value of capital: 1) The market value of loan losses not realized in accounting books, 2) unrealized losses in securities portfolios, and/or 3) unrealized foreign exchange losses; are the sources of funds to be used as capital verified by the regulatory/supervisory authorities? Can the initial or subsequent injections of capital be done with assets other than cash or government securities? Can Initial disbursement of capital be done with borrowed funds?

Capital requirements can influence competition and risk-taking in various ways. First, high initial capital stringency requirements can impose entry barriers for newcomers. This would restrict competition and allow existing banks to accumulate power, resulting in a more prudent, less-risky behavior. Second, higher overall capital requirements are associated with higher fixed costs of running the bank and, consequently, fewer banks will be able to afford these costs. Third, as Bolt and Tieman (2004) illustrate within a dynamic theoretical framework, more stringent capital adequacy requirements lead banks to set stricter acceptance criteria for granting new loans. Fourth, Hellmann *et al.* (2000) suggest that in addition to the capital-at-risk effect, there is an opposite effect that harms franchise value and encourages gambling. On the same line with Hellmann *et al.* (2000), Matutes and Vives (2000) and Repullo (2004) conclude that capital requirements may not be enough and additional regulations such as deposit rate controls, deposit premiums or asset restrictions could be useful in reducing risk within a competitive environment.

$ASSET\_DIV$ is an index measuring whether there are explicit, verifiable, and quantifiable guidelines for asset diversification (e.g., if banks are required to have some minimum diversification of loans among sectors, or if there are sectoral concentration limits); and whether banks can make loans aboard. Higher values of the index indicate more bank asset diversification.

In the robustness tests, we include a variable gauging a percentage of total assets in the banking system that is owned by the government ($PUBLIC\_OWN$). In addition, we also include a series of other political and institutional quality indexes from the WGI database to check for the robustness of the results. These indexes are control of corruption ($CORRUPTION$), government effectiveness (GOV_EFF), political stability and absence of violence/terrorism ($POLITIC$), regulatory quality (REG_QUA), rule of law ($RULE\_LAW$) and voice & accountability ($VOICE\_ACC$). All definition and data sources of all variables can be found in Table 3-1.

3.3.1.2.4 Summary Statistics

Table 3-1 summarizes all definitions and sources of variables as well as their symbols used in this chapter. Table 3-2 presents descriptive statistics of the sample. All variables are winsorized at the 1% and 99% levels. Looking at Table 3-2, we see that the mean log z-score (*Z_SCORE*) is 3.87 and the standard deviation is 1.52. This is a fairly high standard deviation and the wide range in Z-scores suggest that there is considerable variation across countries in the level of bank risk. These statistics of Z-score are quite similar to those reported by Laeven and Levine (2009) and Houston *et al.* (2010). The sample of Laeven and Levine (2009) is smaller with 287 banks in 33 countries and they report 2.85 for the mean of Z-score and 0.99 for the standard deviation. With a large (but smaller than ours) sample of 2,400 banks in 69 countries, Houston *et al.* (2010) report a mean Z-score of 3.24 and a standard deviation of 1.09. According to the alternative measures of bank risk, the means value of the two modified Z-scores are slightly lower when more periods of ROA are incorporated into the calculation of Z-score. Specifically, the mean of Z-score with a four-period rolling window of ROA (*Z_SCORE_4WIN*), which has a value of 3.64, is slightly higher than that of Z-score with a five-rolling period window of ROA (*Z_SCORE_5WIN*), which has a value of 3.50. We also use a ratio of nonperforming loans to total loans (*NPL*) as another alternative measure of bank risk and its mean value is approximately 0.035 (or 3.5%).

The statistics on Table 3-2 also show that the mean value of the depth of credit information sharing index (*DEPTH*) is 5.04 and the median is 5 suggesting that banks in the sample enjoy a high degree of credit information sharing depth. The mean value of private credit bureau coverages (*PRIV*) and public credit registry coverages (*PUB*) are 0.78 (78%) or 0.091 (9.1%), respectively. According to the information environment proxies, the mean of IFRS adoption (*IFRS*) is 0.29, while the mean value of the Business Extent of Disclosure index (*BDI*) is 6.45.

Regarding to our competition measures, the mean of the first competition measure (*COMPET1*), which is transformed from the Lerner index, is around 0.757, showing that competition during the sample period (2005-2013) is quite high. At the same time, the mean value of the second competitive measure (*COMPET2*), which is transformed from the three-largest bank asset concentration index, is 0.185; while, the mean value of the third competitive measure (*COMPET3*), which is transformed from the five-largest bank asset concentration index is 0.224. The mean values of *COMPET2* and *COMPET3* are not in line with the mean of *COMPET1* implying that the competition measure derived from the concentration index may not be comparable to the competition measure derived from the Lerner index. The concentration index can be highly influenced by the differences in the number of banks in the banking system but does not actually reflect the overall market competitiveness.

Furthermore, Table 3-2 reports the sample statistics for control variables. According to the bank-specific variables, the mean log of the total asset (*SIZE*) is 5.96. Less than 25 percent of bank-year observations in the sample has its share of the country's total deposits exceeds 10%, which is the threshold that is considered as too-big-too-fail (*TBTF*). The mean of net loans to total deposits (*LOAN*) is as high as 0.823. And the ratio of cost-to-income (*EFFICIENCY*) is 0.69. According to the country-specific variables, the mean of GDP growth rate (*GDPG*) is 1.2% and the mean of inflation (*INF*) is 3.1%. Although the range of creditor rights index (*CR*) is generally zero to four, the strength of creditor rights is around one to two on average for many countries in the sample. More than 75 percent of the banks' deposits in the sample are insured by their government (*DEPOSIT_INS*). Regulation on capital is quite stringent (*CAPITAL_STR*) for most countries as its mean is 6.83 suggesting that banks in many countries are subjected to stringent capital requirement. Lastly, the mean of banks' asset diversification (*ASSET_DIV*) is 0.34.

In addition to the variables used in the main regression, we also present the summary statistics of other variables used in robustness tests. Regarding a series of political and institutional quality indexes, a control of corruption index (*CORRUPTION*) has a mean value of 1.03, a government effectiveness index (*GOV_EFF*) has a mean value of 1.2, a political stability index (*POLITIC*) has a mean value of 0.372, a regulatory quality index (*REG_QUA*) has a mean value of 1.14, a rule of law index (*RULE_LAW*) has a mean value of 1.17, and lastly a voice and accountability index (*VOICE_ACC*) has a mean value of 0.9. The mean value of a public ownership of bank assets (*PUBLIC_OWN*) is 0.106.

Table 3-3 reports the yearly sample distribution by year of our main variables. The table shows that the sample size is around 10,000 throughout our sample period 2005 to 2013. By examining our main measure of bank risk, Z-Score, across years, the overall trend shows that bank risk increases dramatically from 2008 to 2009 (lower Z-score), which is during the global financial crisis. The results, as confirmed by IMF (2009)[16], imply that bank performance is most affected by the financial crisis during the year of 2009. Furthermore, bank risk gradually decreases in 2010 (rising Z-score), which implies that banks was hit hard by the global financial crisis but has gradually rebounded. Consistent with Z-Score as a measure of bank risk, the trend of NPL as a measure of bank risk shows that a percentage of nonperforming loans increases quite significantly during 2009 and 2010 when the global financial crisis is at its peak.

The trend of the depth of credit information sharing index on Table 3-3 shows that the average is approximately at five to six. When the three measures of banking competition are compared by year, they reveal different trends. The trend of competition as measured by *COMPET1* (inversely related to Lerner index) is ascending between the year 2005 and 2008 suggesting a decreasing in pricing power (lower Lerner index) over time. In other words, the banking markets become more competitive during that period and peak at the year 2008. This trend is similar to the results of Fu *et al.* (2014) who also show that the downward trend of the Lerner index (higher competition) for 14 Asia Pacific economies during the year 2005 to 2008. However, we additionally show that the downward trend in the Lerner index is not limited to only the countries in Asia Pacific but also other regions around the globe. From 2009 onward, the trend of competition as measured by *COMPET1* is descending and smooth in the year 2011 and 2012.

Similar to *COMPET1*, Table 3-3 shows that the trend of competition as measured by *COMPET2* and *COMPET3* (inversely related to banking concentration index) is also ascending over the period of 2005 to 2008. However, the trend continues exhibiting in an ascending order, implying that the banking market is becoming less and less concentrated over time. As noted earlier, the concentration index is largely influenced by the number of banks in the banking system. Thus, the resulting of less concentrated banking market does not necessarily imply less market power, especially those banks who survive from the global financial crisis in 2008-2009. In other words, as the markets become less concentrated, it may have nothing to do with the markets become more competitive. Banks that do not fail

[16] International Monetary Fund, 2009. Global Financial Stability Report, April

during the global financial crisis are usually the more efficient bank, which effectively has lower costs in producing the same output (Beck *et al.* 2006a).

We also check for the correlation between variables. The correlation matrix is shown in Table 3-4, Table 3-5 and Table 3-6. *DEPTH* is positively correlated with *Z_SCORE* and negatively correlated with *NPL*, reflecting that there exists a negative relationship between credit information sharing and bank risk. *PRIV* and *PUB* are also positively associated with *Z_SCORE*. *DEPTH* and *PRIV* are highly correlated. This highly positive correlation suggests that a country with the high depth of credit information tends to have high coverage of private credit bureaus or vice versa. However, each variable enters the regression individually, so the problem of multicollinearity should be less of a concern. Opposite to *PRIV*, *DEPTH* is negatively associated with *PUB*. Regarding the information environment proxies, *DEPTH* is negatively correlated with *IFRS* but negatively correlated with *BDI*. Regarding the banking competition measures, *DEPTH* is negatively associated with all three measures of competition. Moreover, the governance variables (*CORRUPTION*, *GOV_EFF, POLITIC, REG_QUA, RULE_LAW, VOICE_ACC*) exhibit a very strong correlation with one another; therefore, each enters the regression one at a time.

3.3.2 Methodology

To test for our hypothesis H1, which we expect that credit information sharing will reduce bank risk, the regression analysis is expressed as followed:

$$Risk_{i,t} = \beta_0 + \beta_1 CIS_{i,t} + \sum_{k=2}^{6} \beta_k (X_{i,t}^{k}) + \sum_{m=7}^{12} \beta_m (Y_{i,t}^{m}) + \lambda_t + \alpha_i + \varepsilon_{i,t} \qquad (3\text{-}9)$$

Where i and t indicates the i^{th} bank in year t; *Risk* is measured by Z-Score index (*Z_SCORE*), which is inversely related to banking risk, so that the higher the Z-Score the lower the bank risk; *CIS* is a credit information sharing variable proxied by the depth of credit information sharing index (*DEPTH*); *X* contains bank-specific variables, consisting of bank's size (*SIZE*), bank's size squared (*SIZE_SQR*), too-big-to-fail dummy (*TBTF*), a ratio of loan to deposits (*LOAN*) and a ratio of cost-to-income (*EFFICIENCY*); *Y* contains country-specific variables, consisting of GDP growth (*GDPG*), inflation (*INF),* creditor rights index (*CR*), deposit insurance dummy (*DEPOSIT_INS*), capital stringency index (*CAPITAL_STR*) and asset diversification index (*ASSET_DIV*); λ_t is the year fixed effects; α_i is the individual effects or the time-invariant component of the error term; and ε is an idiosyncratic error term or time-varying component of the error term. The coefficient β_1 reflects the impact of credit information sharing on bank risk. Higher Z-score index implies lower bank risk; thereby, according to the hypothesis H1, we expect the sign of β_1 to be positive such that credit information sharing reduces bank risk.

To test for our hypothesis H2, which we expect that high transparent information environment will attenuate the impact of credit information sharing on bank risk, we augment Equation (3-9) with one of the two proxies of information environment and their interactions with the credit information sharing measure. The new regression model thus expresses as followed:

$$Risk_{i,t} = \beta_0 + \beta_1 CIS_{i,t} + \beta_2 ASYM_{i,t} + \beta_3 ASYM_{i,t} * CIS_{i,t} + \sum_{k=4}^{8} \beta_k (X_{i,t}^{k}) + \sum_{m=9}^{14} \beta_m (Y_{i,t}^{m}) + \lambda_t + \alpha_i + \varepsilon_{i,t} \quad (3\text{-}10)$$

Where i and t indicates the i[th] bank in year t; *Risk* is measured by Z-Score index (*Z_SCORE*), which is inversely related to banking risk, so that the higher the Z-Score the lower the bank risk; *CIS* is a credit information sharing variable proxied by the depth of credit information sharing index (*DEPTH*); *ASYM* represents one of the two proxies of information environment, namely IFRS adoption ($IFRS$) and the business extent of disclosure index (BDI). *X* contains bank-specific variables, consisting of bank's size (*SIZE*), bank's size squared (*SIZE_SQR*), too-big-to-fail dummy (*TBTF*), a ratio of loan to deposits (*LOAN*) and a ratio of cost-to-income (*EFFICIENCY*); *Y* contains country-specific variables, consisting of GDP growth (*GDPG*), inflation (*INF),* creditor rights index (*CR*), deposit insurance dummy (*DEPOSIT_INS*), capital stringency index (*CAPITAL_STR*), asset diversification index (*ASSET_DIV*); λ_t is the year fixed effects; α_i is the individual effects or the time-invariant component of the error term; and ε is an idiosyncratic error term or time-varying component of the error term. The coefficient β_3 reflects the extent to which degree of information environment moderates the impact of credit information sharing on bank risk. Therefore, according to the hypothesis H2, we expect the sign of β_3 to be negative for both

IFRS and *BDI*. Should the sign of the interaction term β_3 is significantly negative, the impact of credit information sharing on bank risk is less pronounced in a more transparent information environment.

To test for our hypothesis H3, which we expect that the impact of credit information sharing on bank risk is more pronounced in more competitive banking market, we augment Equation (3-9) with an index measuring the level of banking competition and its interaction with the credit information sharing measure. The new regression model is thus as followed:

$$Risk_{i,t} = \beta_0 + \beta_1 CIS_{i,t} + \beta_2 COMPET1_{i,t} + \beta_3 COMPET1_{i,t} * CIS_{i,t} + \sum_{k=4}^{8} \beta_k (X_{i,t}^{k}) + \sum_{m=9}^{14} \beta_m (Y_{i,t}^{m}) + \lambda_t + \alpha_i + \varepsilon_{i,t} \quad (3\text{-}11)$$

Where i and t indicates the i[th] bank in year t; *Risk* is measured by Z-Score index (*Z_SCORE*), which is inversely related to banking risk, so that the higher the Z-Score the lower the bank risk; *CIS* is a credit information sharing variable proxied by the depth of credit information sharing index (*DEPTH*); *COMPET1* is an index measuring the level of banking competition which is transformed from the Lerner index. The higher the index the higher the competition. *X* contains bank-specific variables, consisting of bank's size (*SIZE*), bank's size squared (*SIZE_SQR*), too-big-to-fail dummy (*TBTF*), a ratio of loan to deposits (*LOAN*) and a ratio of cost-to-income (*EFFICIENCY*); *Y* contains country-specific variables, consisting of GDP growth (*GDPG*), inflation (*INF),* creditor rights index (*CR*), deposit insurance dummy (*DEPOSIT_INS*), capital stringency index (*CAPITAL_STR*), asset diversification index (*ASSET_DIV*); λ_t is the year fixed effects; α_i is the individual effects or the time-invariant component of the error term; and ε is an idiosyncratic error term or time-varying component of the error term. The coefficient β_3 reflects the extent to which degree of banking competition moderates the impact of credit information sharing on bank risk; thereby, according to H2, we expect the sign of β_3 to be positive such that the impact of credit information sharing on bank risk more pronounced with high competitive banking environment.

In the robustness test, we re-estimate Equation (3-9) to Equation (3-11) with a few modifications and augmentations. We replace Z-score with alternative measures of bank risk, which consist of two modified Z-score index (*Z_SCORE_4WIN* and *Z_SCORE_5WIN*) and a ratio of non-performing loans to total loans (*NPL*). Moreover, we use alternative variables measuring the level of credit information sharing, consisting of a private credit bureau coverage (*PRIV*) and a public credit registry coverage (*PUB*). Furthermore, we add some more country-level controls related to political and institutional quality indices (*CORRUPTION, GOV_EFF, POLITIC, REG_QUA, RULE_LAW* and *VOICE_ACC*) and a variable gauging a percentage of total assets in the banking system that is owned by the government (*PUBLIC_OWN*). We also provide an instrumental variable regression by employing a legal origin dummy (*LEGALORIGIN*), ethnic fractionalization (*ETHNIC_FRAC*) and latitude (*LATITUDE*) as instrumental variables for credit information sharing and bank risk.

3.4 Empirical Results, Robustness Tests and Additional Test

3.4.1 Empirical Results

3.4.1.1 The Impact of Credit Information Sharing on Bank Risk

Before proceeding to the regression results, we conduct model selection and diagnostic tests, which are shown on Table 3-7. All tests are applied to Equation (3-9) without interaction terms and the chosen estimation technique are then applied to Equation (3-10) and (3-11)[17]. As shown on Table 3-7, the estimators from the pool OLS regression are biased and inconsistent. Also, the fixed effect regression is preferable to the random effect regression. Furthermore, to account for the problems of heteroscedasticity and serial correlation, we adjust standard errors that are robust to heteroscedasticity and cluster standard errors at bank-level to account for within-cluster correlation of the error term[18]

The regression results of Equation (3-9) are displayed in Table 3-8 regarding the impact of credit information sharing on bank risk. T-statistics are reported in parentheses. Bank risk is measured by *Z_SCORE* (Once again, a higher *Z_SCORE* implies lower risk) and the level of credit information sharing is measured by *DEPTH*. The coefficient of *DEPTH* (or β_1 in Equation (3-9)) is positive and significant (at 5% level), showing that

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[17] Adding interaction terms would not significantly change the overall results of the tests much.
[18] More detail of model selection tests and diagnostic tests can be found in the Appendix F.

Z_SCORE increases with higher *DEPTH*. This result is consistent with our hypothesis H1, suggesting that bank risk is lower with higher level of credit information sharing.

By assessing the marginal effect of credit information sharing on bank risk holding all other variables at their sample mean, we find that a one-unit increase of *DEPTH* is associated with a change in *Z_SCORE* of 0.117. Hence, switching from a regime without credit information sharing to a regime with fully-fledged credit information sharing (*DEPTH*=6) can increase bank Z-score by up to 0.702. This finding lends support to the argument that credit information sharing can decrease bank risk because information sharing among banks helps alleviate adverse selection problems in lending and the post-lending moral hazard problems (Pagano & Jappelli 1993; Padilla & Pagano 1997), increase the incentives for debt repayment (Klein 1992; Vercammen 1995; Padilla & Pagano 2000) and reduce over-borrowing (Bennardo *et al.* 2009, 2014).

Our finding is in line with previous studies that attempt to examine the effect of credit information sharing on bank risk. Regarding to the early empirical analysis of the effects of information sharing on credit markets, Jappelli and Pagano (2002) support that credit risk is lower in countries where lenders share information about their borrowers. However, there is a shortcoming of the results of Jappelli and Pagano (2002) because of the weak quality of their proxy of a default rate (or credit risk), which is based on the International Country Risk Guide (ICRG) survey of leading international bankers. The ICRG indicator is imperfectly correlated with the likelihood of default on bank loans and it may also reflect other financial risks. Recently, with smaller sample and different sample period, Houston *et al.* (2010) utilize bank-level data in 69 countries and measure bank risk with a better indicator, Z-Score, which is similar to the one we use in this analysis. They also find that bank risk is positively related to credit information sharing. Our study complements Houston *et al.* (2010) by using recent data and more banks and countries in the sample. Similarly, based on cross-country empirical investigation, Büyükkarabacak and Valev (2012) also support the contributed effect of credit information sharing to the likelihood of banking crises by showing that credit information sharing reduces the likelihood of banking crises.

Investigating the coefficients of various control variables, we find a few interesting results. The significantly positive coefficient for bank size (*SIZE*) suggests that larger banks face less risk. Laeven and Levine (2009), Houston *et al.* (2010) and Fu *et al.* (2014) also find the same result. In addition, by including a square of bank size (*SIZE_SQR*), we find an inverse U-shape relationship between bank size and bank risk. Banks that are classified as too-big-too-fail (*TBTF*) engage in more risk-taking. Less efficient banks with high cost-to-income ratio (*EFFICIENCY*) tends to be relatively riskier. Regarding to macroeconomic variables, we find that higher inflation rate (*INF*) is associated with higher risk.

By considering banking regulatory environment, the results reveal several interesting results. First of all, the evidence does not show that an existence of deposit insurance regime (*DEPOSIT_INS*) is significantly associated with bank risk, contrasting the moral hazard argument stating that bank act imprudently when a financial safety net is available. As point out by Barth *et al.* (2006), a deposit insurance regime intensifies the moral hazard problem in banking because depositors no longer face the risk of losing their savings, which diminishes their incentives and efforts to monitor bank activities (Houston *et al.* 2010). Our finding about the relationship between deposit insurance and bank risk is inconsistent with previous studies (e.g. Demirgüç-Kunt and Detragiache (2002)). Secondly, we find that the overall capital stringency (*CAPITAL_STR*) is significantly and positively related to lower bank risk. This suggests that stringent capital requirement promote more bank stability. Lastly, bank risk is lower with higher asset diversification (*ASSET_DIV*) indicating that banks are less risky when the regulation on asset diversification allows banks to diversify asset across sectors and aboard.

3.4.1.2 The Impact of Information Asymmetry on the Relationship between Credit Information Sharing and Bank Risk

Information asymmetry can be problematic for banks since the adverse selection and moral hazard problems in lending are exacerbated. Nonetheless, asymmetric information can be less of a problem when the information environment is more transparent. When the information environment is more transparent, the benefit of credit information sharing can potentially decrease. In the previous section, we show that credit information sharing reduces bank risk because the sharing scheme helps to overcome the information problem and bridge the information gaps between banks and borrowers, such that banks can lend safely and borrowers behave well.

In this section, we present the regression results of Equation (3-10) testing whether the relationship between credit information sharing and bank risk varies with different degree of information environment. The results are shown Table 3-9. T-statistics are reported in parentheses. Bank risk is measured by *Z_SCORE* (Once again, a higher *Z_SCORE* implies lower risk) and the level of credit information sharing is measured by *DEPTH*. *IFRS* and *BDI* are used as proxies for information environment transparency.

The results with *IFRS* as a proxy of information environment are presented in the column 2 and column 3 of Table 3-9. The coefficient of the interaction term between *DEPTH* and *IFRS* (or β_3 in Equation (3-10)) is negatively significant (at 1% level). Since the value one of the *IFRS* dummy proxies for more transparent information environment, the negative coefficient of the interaction indicates that *IFRS* attenuates the impact of credit information sharing on bank risk. This result supports our hypothesis H2 that the impact of credit information sharing on bank risk is less pronounced in a country with more transparent information environment as proxied by mandatory IFRS adoption. We also evaluate the moderating effect of *IFRS* on the relationship between credit information sharing and bank risk. When the country does not adopt IFRS, a one-unit increase of *DEPTH* will increase *Z_SCORE* by 0.495. However, when the country adopts IFRS, a one-unit increase of *DEPTH* will increase *Z_SCORE* by 0.087. That is 0.408 or approximately 82.4% less pronounced with IFRS adoption.

The results with *BDI* as a proxy of information environment are presented in the column 4 and column 5 of Table 3-9. The coefficient of the interaction term between *DEPTH* and *BDI* (or β_3 in Equation (3-10)) is negative and significant (at 5% level). As higher *BDI* indicates more transparent information environment, the negatively significance of the interaction term suggests that *BDI* mitigate the impact of credit information sharing on bank risk. To measure the moderating effect of *BDI* on the relationship between credit information sharing and bank risk, the interaction term is evaluated at the 25th and 75th percentiles of *BDI*. *DEPTH* can increase bank *Z_SCORE* by between 0.035 and 0.104, depending on the degree of *BDI*. Specifically, a unit-increase in *DEPTH* is associated with a 0.104 increase in *Z_SCORE* when *BDI* is at the 25th percentile. The impact reduces to 0.035 when *BDI* is at the 75th percentile. We can securely conclude that the benefit of credit information sharing decreases with the business extent of disclosure index. In other words, the impact of credit information sharing on bank risk is less pronounced when the information environment is more transparent. This evidence strengthens our hypothesis H2.

3.4.1.3 The Impact of Banking Competition on the Relationship between Credit Information Sharing on Bank Risk

As explained in the literature review section, the problem of adverse selection and moral hazard associated with both borrowers and banks are more intense in a competitive banking market (Broecker 1990; Nakamura 1993; Riordan 1995; Marquez 2002). Also, banks in less competitive banking market are more likely to lend more efficient through better screening process (Cetorelli & Peretto 2000; Cetorelli & Peretto 2012) and have a stronger incentives to monitor the projects of borrowers and even establish a long-term relationships (Petersen & Rajan 1995; Von Thadden 1995; Caminal & Matutes 2006). Therefore, the impact of credit information sharing on bank risk may be more pronounced when the banking market is more competitive.

In this section, we present the regression results of Equation (3-11) testing whether the relationship between credit information sharing and bank risk varies with different level of banking competition. To examine the potential interactive effects between credit information sharing and banking competition, we construct our first measure of banking competition, *COMPET1*, based on the Lerner index and it is calculated as one minus Lerner index. Therefore, higher index can be translated directly into higher level of banking competition. The results are shown in Table 3-10. T-statistics are reported in parentheses. Bank risk is measured by *Z_SCORE* (Once again, a higher *Z_SCORE* implies lower risk) and the level of credit information sharing is measured by *DEPTH*.

The column 3 of Table 3-10 reports the result of the interaction between *DEPTH* and *COMPET1* (or β_3 in Equation (3-11)). The coefficient of the interaction term is positive and significant (at 1% level), indicating that the impact of credit information sharing on bank risk is higher with an increase in the degree of banking competition. This result lends support to our hypothesis H3 that the role of credit information sharing on bank risk is more pronounced in a more competitive banking market. To measure the moderating effect of banking competition, the interaction term is evaluated at the 25th, 50th and 75th percentile of *COMPET1*. When *COMPET1* is at 25th percentile, a one-unit increase in *DEPTH* increases

Z_SCORE by 1.022. This effect increases to 1.109 and 1.189, when *COMPET1* is at 50th and 75th, respectively. The significant interaction between *DEPTH* and *COMPET1* suggests that the impact of credit information sharing on bank risk is more pronounced when the banking market become more and more competitive. With this regard, we can conclude that the benefit of credit information sharing on bank risk increases with banking competition.

3.4.2 Robustness Tests

In this section, we perform several robustness tests of our main results. First, we employ alternative measures of bank risk, consisting of two modified Z-Score (*Z_SCORE_4WIN* and *Z_SCORE_5WIN*) and a ratio of non-performing loans to total loans (*NPL*). Second, we use two other measures of credit information sharing level, consisting of private credit bureau coverage (*PRIV*) and public credit registry coverage (*PUB*). Third, we replace our main competition measure by three-largest banking asset concentration index (*COMPET2*) and five-largest banking asset concentration index (*COMPET3*) in separate regressions. Fourth, we augment each of Equation (3-9), (3-10) and (3-11) with additional variables to control for factors that can potentially influence bank risk. Fifth, we provide a subsample analysis for robustness checks of results regarding to our hypothesis H2 and H3. The subsamples are classified by proxies of information environment (*IFRS* and *BDI*) and the banking competition measure (*COMPET1*). Sixth, we provide another subsample analysis by excluding banks in the USA because majorities of banks in the sample are USA's banks. Lastly, an instrumental variable approach is employed to check for the robustness of the main results.

3.4.2.1 Alternative Measures of Bank Risk

Regarding to the first two alternative measure of bank risk, we re-calculate the Z-Score and generate these two additional variables, *Z_SCORE_4WIN* and *Z_SCORE_5WIN*. To obtain *Z_SCORE4WIN*, we use data of ROA in the current year and three previous years (t, t-1, t-2 and t-3) to compute the standard deviation of ROA at time t and use that to compute Z-Score. To obtain *Z_SCORE_5WIN*, we use data of ROA in the current year and four previous years (t, t-1, t-2, t-3 and t-4) to compute the standard deviation of ROA at time t and use that to compute Z-Score.

The results with *Z_SCORE_4WIN* as a dependent variable is displayed in Table 3-11, while the results with *Z_SCORE_5WIN* as a dependent variable is shown in Table 3-12. Overall, the main findings are still unchanged. Specifically, the results in the column 1 of each table support our hypothesis H1 because the coefficients of *DEPTH* are still positive and significant, although both coefficients are less in magnitude and less significant in the regression with *Z_SCORE_5WIN*. The results in the column 2 to the column 5 of each table also support our hypothesis H2 because the coefficients of the interaction term between *DEPTH* and proxies of information environment (IFRS & BDI) are negative and significant. According to the hypothesis H3, the significantly positive coefficients of the interaction term between *DEPTH* and *COMPET1* in the column 6 and the column 7 of each table also support that bank risk is lower with credit information sharing level when the banking market become more and more competitive.

Next, we replace Z-Score with a ratio of non-performing loans to total loans (*NPL*), which is another variable that is widely in gauging bank risk (Berger *et al.* 2009; Jeon & Lim 2013). The regression results are presented in Table 3-13. The result in the column 1 shows that the coefficient of *DEPTH* is negative and significant (at 5% level). This result supports our hypothesis H1 that bank risk is lower with higher level of credit information sharing. A one-unit increase of *DEPTH* is associated with a 1% reduction in *NPL*. According to the hypothesis H2, the results in the column 3 support that the impact of credit information sharing on bank risk is less pronounced with more transparent information environment as proxied by IFRS adoption. Specifically, the coefficient of the interaction term between *DEPTH* and *IFRS* is negative and significant (at 10% level) meaning that the impact of *DEPTH* on *NPL* is lower when *IFRS* dummy is equal to one. Similarly, the negatively significance of the interaction term between *DEPTH* and *BDI* in the column 5 shows that the impact of *DEPTH* on *NPL* is lower with higher *BDI*. This result also supports the hypothesis H2 that the impact of credit information sharing on bank risk is less pronounced with more transparent information environment as proxied by BDI.

The regression with *NPL* as a dependent variable also support the hypothesis H3 that the impact of credit information sharing on bank risk is less pronounced with higher banking competition. The regression results are reported in the column 7 of Table 3-13. The coefficient of the interaction term between *DEPTH* and *COMPET1* is negative and significant (at 5% level). The coefficient of *DEPTH* itself is not significant, but it is only significant through its interaction with *COMPET1*. Thus, the effect of credit information sharing on bank risk is insignificant when there is no banking competition (when *COMPET1* = 0), which is quite impossible practically and intuitively, but such impact is significant with at least some level of banking competition (when *COMPET1* > 0). The significantly negative coefficient of the interaction term between *DEPTH* and *COMPET1* suggests that credit information sharing reduces bank risk more with higher level of banking competition. However, if the level of banking competition goes below 0.511 (*COMPET* < 0.511), credit information sharing in turn increase bank risk (higher *NPL*). Impliedly, credit information sharing may decrease the informational advantage of banks in a low competitive banking market. As suggested by Petersen and Rajan (1995), banks in a low competitive banking market tend to enjoy long-term lending relationship with borrowers due to potential intertemporal surplus sharing. These lending relationships help banks acquire privately important credit information about their borrowers that is not known to other banks. With more disclosure through credit information sharing, the lending relationships may no longer exist as private information is known to other banks, so the banking market become more fiercely competitive (Petersen & Rajan 1995).

3.4.2.2 Alternative Measures of Credit Information Sharing

Instead of using depth of credit information sharing index (*DEPTH*) as the proxy for the level of credit information sharing, we employ private credit bureau coverage (*PRIV*) and public credit bureau coverage (*PUB*). The regression results with *PRIV* is shown in Table 3-14. Noted that higher *PRIV* indicates higher level of credit information sharing. According to the hypothesis H1, the result in the column 1 still supports that bank risk is lower with higher level of credit information sharing. Economically, a one-percentage increase in *PRIV* is corresponding to a 0.00309 increase in *Z_SCORE.* Consistent with the hypothesis H2, the coefficient of the interaction term between *PRIV* and *IFRS* as well as the interaction term between *PRIV* and *BDI* are negative and significant. Consistent with the hypothesis H3, the coefficient of the interaction term between *PUB* and *COMPET1* is positive and significant (at 1% level).

The regression results with *PUB* is shown in Table 3-15. Noted that higher *PUB* indicates higher level of credit information sharing. Notably, we find no significant impact of compulsory information sharing via public credit registry on bank risk throughout the model specification. One possible reason is that sharing information has pros and cons. The cost for a bank is that its competitor may learn something about that bank's portfolio and customers, whereas the benefit is that the bank is able to access to wide profile of borrowers cheaply and may be able to make more informed lend decision[19]. Moreover, banks generally invest and acquire costly information about customers to establish a profitable lending relationship. Given that relationships tie borrowers in to a lender, that lender may exert a type of monopoly power (Majnoni *et al.* 2004). When public credit registries force banks to share this information, it reduces the monopoly rents available that banks can extract from their lending relationship (Petersen & Rajan 1995; Majnoni *et al.* 2004). As a result, banks' profits could shrink and they have an incentive to pursue riskier projects to compensate for the losses and to accumulate capital cushions (Keeley 1990; Allen & Gale 2004). According to our results with *PUB*, the benefits may offset the costs with compulsory sharing via public credit registries, so that they have no impact on bank risk.

Also, there is some distinction between a private credit bureau and a public credit registry that may lead to the significance of *PRIV* and the insignificance of *PUB*. Generally, a public credit registry has limitations when compared to a private credit bureau. It is quite common for public credit registries to set a minimum loan size and therefore to collect information only on loans in excess of this amount (Miller, 2003). Furthermore, the information from public credit registries consists mainly of credit data and is disseminated in consolidated form (so that details about individual loans are not available). In addition, public registries only collect data from supervised institutions like banks. In contrast, private credit bureaus offer details on individual loans and merge credit data with data from other sources (e.g., firms, leasing and finance companies, retail establishments, courts, tax authorities, and financial statements), though they are less comprehensive in coverage (Jappelli and Pagano, 2002). More importantly, in most cases, historical data are not made available to financial institutions via the public credit registries (Miller, 2003).

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[19] One may argue that the benefits of sharing negative information absolutely exceed the costs. However, the benefits of sharing positive information may not always exceed the costs.

3.4.2.3 Alternative Measures of Banking Competition

In this section, we provide additional robustness checks for the hypothesis H3 by employing two alternative measures of banking competition, which are previously used to measure the degree of banking competition. These two variables are the three-largest bank asset concentration index and the five-largest bank asset concentration index. The three-largest bank asset concentration index is converted into a competition measure by subtracting it from one to obtain *COMPET2.* Similarly, the five-largest bank asset concentration index is converted into a competition measure by subtracting it from one to obtain *COMPET3*.

The regression results using each of *COMPET2* and *COMPET* 3 as a measure of banking competition are reported in Table 3-16. We do not see the interaction term between *DEPTH* and *COMPET2* as well as the interaction term between *DEPTH* and *COMPET3* to be significant. Although the results with *COMPET2* and *COMPET3* may not produce desire results, they pose no problem to the main results. This is because there is a growing consensus that concentration measures are not good proxies for measuring bank competition (Berger *et al.* 2004; Claessens & Laeven 2004; Beck *et al.* 2006a). The banking concentration measures, like Herfindhal Hirschman Index (HHI) and N-bank concentration ratios[20], have also been viewed as ambiguous indicators of market power/competition because they ignore the relationship between revenue and market contestability at the bank-level (Beck *et al.* 2006a; Berger *et al.* 2009; Skully & Perera 2012). Specifically, these measures of concentration do not take into account the competitive behavior of banks in a way that banks with different ownership behave differently and that banks might not compete directly with each other in the same line of business (Beck 2008). Furthermore, the concentration measures are computed at nationwide level which may not always coincide with the market power exercised at the local level (Berger *et al.* 2009).

[20] N-bank is the number of banks.

3.4.2.4 Additional Control Variables

Moreover, we provide additional robustness tests by controlling more factors that could potentially affect bank risk. First, we add a series of macro institutional indexes in our model to test the robustness of the results. These variables are six components of the World Governance Indicators (Kaufmann *et al.* 2011), which capture different aspects of the institutional environment. The detailed definition of the indexes can be found in the data section. These governance indicators enter the regression individually (one at a time) because they are highly correlated with one another. In addition, we also include a percentage of public ownership of bank assets in the country' banking system.

Table 3-17 presents the regression results for Equation (3-9) with additional control variables. Consistent with the hypothesis H1, the coefficient of *DEPTH* is still positive and significant (at 5% and 10% level) with some variation in the impact magnitude. Table 3-18 and Table 3-19 present the regression for Equation (3-10) with additional control variables. Consistent with the hypothesis H2, the coefficient of the interaction term between *DEPTH* and *IFRS* as well as the interaction term between *DEPTH* and *BDI* are still negative and significant (at 1% and 5% level) with some variation in the impact magnitude. Table 3-20 presents the regression for Equation (3-11) with additional control variables. The coefficients of the interaction term between *DEPTH* and *COMPET1* are still positive and significant (at 1% level) in all cases. Although the magnitude of *DEPTH* may be lower with additional control variables, all our main results are still upheld.

Interestingly, we find that better control of corruption (*CORRPUTION*), effective government (*GOV_EFF*) and good regulatory quality (*REG_QUA*) are associated with lower bank risk. The finding also reveals that bank risk increases with a higher percentage of public ownership of bank assets (*PUBLIC_OWN*). This suggests that state-owned banks might be seen as vehicles for raising capital to finance projects with high social returns, but possibly high-risk and low-profit returns (Shleifer & Vishny 1986; Shleifer & Vishny 1998).

3.4.2.5 Subsample Analysis

Beside interacting results, we also provide a subsample analysis. We classify the sample based on each proxy of information environment. Based on *IFRS* dummy, one subsample consists of observations with *IFRS* proxied for more transparent information environment, while another subsample consists of observations with *NON-IFRS* proxied for low transparent information environment. Based on *BDI*, one subsample consists of observations with the value of *BDI* above the sample median to proxy for high transparent information environment, while another subsample consists of observations with the value of *BDI* below the sample median to proxy for low transparent information environment.

Table 3-21 reports the subsample analysis based on *IFRS* and *BDI.* The subsample with *NON-IFRS* in the column1 shows that the coefficient of *DEPTH* is positive and significant at 5% level, whereas the subsample with *IFRS* in the column 2 shows that the coefficient of *DEPTH* is positive but significant at 10% level. In comparison to the subsample with *NON-IFRS*, the coefficient of *DEPTH* in the subsample with *IFRS* is less significant. This suggests that the impact of credit information sharing on bank risk is more pronounced with *NON-IFRS* adoption. The magnitude of *DEPTH* in the *NON-IFRS* sample is also larger than the one in the *IFRS* sample.

On the same table, the subsample with *LOW BDI* in the column 3 shows that the coefficient of *DEPTH* is positive and significant at 1% level, but the coefficient of *DEPTH* in the subsample with *HIGH BDI* shown in the column 4 is not significant. This suggests that not only the impact of credit information sharing on bank risk is more pronounced with *LOW BDI*, but such impact is not even significant with *HIGH BDI*. Overall, our main results related to the hypothesis H2 are still supported with the subsample analysis based on IFRS and BDI as proxies of information asymmetry.

Table 3-22 presents the subsample analysis based on the banking competition measure. The sample is divided into top 25th and bottom 25th percentile of *COMPET1* shown in the column 1 and the column 2, respectively. We find that the coefficient of *DEPTH* is only significant in the subsample with top 25th percentile of *COMPET1*, while it is not significant in the subsample with bottom 25th percentile of *COMPET1*. This suggests that the impact of credit information sharing on bank risk is only significant and pronounced when the degree of banking market competition is high. We confirm the results with additional subsamples classified by top and bottom 30th percentile and top and bottom 40th percentile of *COMPET1*. They are displayed in the column 3 to 6. The findings all show that the coefficients of *DEPTH* are only significant in the subsample with top 30th and top 40th

percentile of *COMPET1*. These results corroborate that the impact of credit information sharing on bank risk is only significant and pronounced when the degree of banking market competition is high. Thus, the subsample analysis based on the banking competition measure *COMPET1* still support our main results related to the hypothesis H3.

3.4.2.6 Non-USA Sample

Since the sample comprises of numerous banks in the USA, the main results may be driven by banks in the USA. Thus, we subsample by excluding banks in the USA and re-estimate each of Equation (3-9), (3-10) and (3-11). The results are shown on Table 3-23. The number of the observation shrinks by almost half. Overall, the results show that exclusion of banks in the USA does not change our main results. On the column 1, the magnitude of *DEPTH* coefficient in the sample without banks in the USA is even slightly higher than the one in the main sample.

Economically, a one-unit increase in *DEPTH* is associated with a 0.124 increase in *Z_SCORE*. When the country does not adopt IFRS, a one-unit increase of *DEPTH* will increase *Z_SCORE* by 0.48. However, when the country adopts IFRS, a one-unit increase of *DEPTH* will increase *Z_SCORE* by 0.169. That is 0.311 or approximately 64.7% less pronounced with IFRS adoption. By evaluating the interaction term between *DEPTH* and *BDI* at the 25th percentile and 75th percentile of *BDI*, we find that a one-unit increase in *DEPTH* is associated with a 0.151 increase in *Z_SCORE* when *BDI* is at the 25th percentile. The impact reduces to 0.09 when *BDI* is at the 75th percentile. In addition, by assessing the interaction term between *DEPTH* and *COMPET1* at the 25th percentile and 75th percentile of *COMPET1*, the results show that a one-unit increase in *DEPTH* is associated with a 1.128 increase in *Z_SCORE* when *COMPET1* is at the 25th percentile. The impact increases to 1.314 when *COMPET1* is at the 75th percentile.

3.4.2.7 Instrumental Variable Approach

There could be a reverse causality between credit information sharing and bank risk. This creates a problem of endogeneity[21]. Based on the existing literature on law and finance (Easterly & Levine 1997; LaPorta *et al.* 1998; La Porta *et al.* 1999; Beck *et al.* 2003; Acemoglu & Johnson 2005), we employ legal origins, ethnic fractionalization and latitude as instrumental variables for *DEPTH*[22]. Rather than using fixed effects estimations, we use a two-stage least squares (2SLS) with pooled OLS estimations because our instruments are time-invariant.

Initially, we test whether *DEPTH* is endogenous by performing the Durbin-Wu-Hausman test of endogeneity. The test shows that the p-value is 0.5695 so the null hypothesis cannot be rejected. Thus, we can treat depth of credit information sharing as exogenous. Nonetheless, we perform robustness tests for Equation (3-9) to (3-11) by employing an instrumental variable approach. The results are presented in Table 3-24, Table 3-25 and Table 3-26. Each table also presents the relevance and validity tests of our instruments.

We perform the F-tests of the excluded instruments in the corresponding first-stage regression to see whether they are relevant. In each table of results, the F-tests show that the null hypothesis is rejected at the 1% level in all regressions. Moreover, we test for the validity of the instruments by performing the Hansen J-test of over-identifying restrictions. We can see that the J-test in all tables cannot be rejected suggesting that the instruments are valid instruments, uncorrelated with the error term and correctly excluded from the estimated equation.

Once we verify that our instruments are relevant and valid, we proceed to the IV regression results of each table. First, we analyze the IV regression results for Equation (3-9). On Table 3-24, the first column reports the second stage regression, while the second column reports the first stage regression. The main result is still robust and consistent with our first hypothesis H1. The coefficient of *DEPTH* remains positive and significant. The result with

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[21] However, the reverse causality between credit information sharing and bank risk is less likely because we explore the impact of credit information sharing agencies on bank risk of individual bank firms. Thus, the endogeneity problem is less of a concern.
[22] Refer to Appendix G for the rationales behind selecting instruments

IV approach confirms our main finding that bank risk decreases with credit information sharing. Moreover, the IV coefficient are much larger than the coefficient of the fixed effect regression, indicating the presence of potential measurement error, which inflates the IV coefficient. Nonetheless, our conclusion does not depend on the instrumentation approach because *DEPTH* is not endogenous and poses no concern of endogeneity.

For Equation (3-10) and (3-11), we split the sample into two subsamples based on each of information environment proxies and the banking competition measure. Table 3-25 display the regression results for Equation (3-10). The first four columns of Table 3-25 present the IV regressions of two subsamples that are split based on *IFRS* as a proxy of information environment transparency. The results are robust and consistent with our second hypothesis H2. The coefficient of *DEPTH* is only significant in the subsample without the mandatory IFRS adoption suggesting that the impact of credit information sharing on bank risk is more pronounced when the information environment is less transparent. Similar results are applied to the subsample based on *BDI*. In the column 5 to 8 of Table 3-25, the coefficient of *DEPTH* is only significant in the subsample with *LOW BDI* suggesting that the impact of credit information sharing on bank risk is more pronounced when the information environment is less transparent.

The regression results of Equation (3-11) are shown in Table 3-26. The table presents the IV regressions of two subsamples which are split based on top and bottom 30^{th} percentile of *COMPET1*. Top 30^{th} percentile of *COMPET1* is corresponding to high degree of banking competition (*HIGH COMPET1*), whereas bottom 30^{th} percentile of *COMPET1* is corresponding to low degree of banking competition (*LOW COMPET1*). Consistent with the hypothesis H3, the coefficient of *DEPTH* is positive and significant in the subsample with *HIGH COMPET1*. This result suggests that the impact of credit information sharing on bank risk is more pronounced in the subsample with high degree of banking market competition.

3.4.3 Additional Test

In this section, we provide one additional result regarding the potential interaction effect between credit information sharing and creditor rights (*CR*) on bank risk. Houston *et al.* (2010) find that stronger creditor rights through the legal system promotes bank risk. They argue that stronger creditor rights may induce banks to extend loans to a wider and riskier set of borrowers. When creditors are greatly protected in the event of default, they are more willing to lend to riskier borrowers with poorer credit ratings. This effect may raise the average expected default rate. If the increased average expected recovery does not offset the increased average expected default, stronger creditor rights will lead to an increase in bank risk. Stronger creditor protection also decreases the level of banks' incentive to monitor their borrowers because marginal benefit of monitoring is lower and the losses in the state of default decreases.

To support his argument, Houston *et al.* (2010) show that there is an interaction effect between credit information sharing and creditor rights on bank risk. They show that the impact of credit rights on bank risk is attenuated by credit information sharing. More specifically, information sharing helps reduce adverse selection and post-lending moral hazard problems; therefore, the potential risk of any given loan is lower with greater level of credit information sharing. Also, information sharing itself works as a post-lending disciplining/monitoring device for borrowers. Thus, this reduces the impact of weaker post-lending monitoring caused by stronger creditor protection.

Following the same line of argument, we argue that the impact of credit information sharing on bank risk is more pronounced with stronger creditor rights. Since stronger creditor rights reduces banks' incentive to monitor and increases the willingness to extend to a wider and riskier set of borrowers, the benefits of credit information sharing on bank risk should be more pronounced with stronger creditor rights. Consistent to our argument, in a subsample analysis shown in Table 3-27, we find that the impact of credit information sharing on bank risk is more pronounced with stronger creditor protection. By classifying the sample into two groups, we show that the coefficient of *DEPTH* is positive and only significant (at 1% level) in a sample with high creditor rights index.

3.5 Conclusion

The study in this chapter explores the impact of credit information sharing on bank risk. The theory argues that credit information sharing alleviates adverse selection and moral hazard. Banks can lend safely with better judgment on their lending decision. Borrowers also become more disciplined and put more effort to service debts, such that the likelihood of borrower defaults reduces. At the same times, credit information sharing might lead to lower lending standards and the entry of riskier borrowers in the credit markets. Thus, credit information sharing might increase or decrease bank risk.

As suggested by the results in chapter 2, credit information sharing facilitates lending decision and encourages banks to extend more credits. Providing more credits may result in higher access to credit for riskier borrowers, and thereby increase bank risk. However, the results presented in this chapter suggests that credit information sharing among banks does not necessarily increase bank risk. By employing a sample of 15,558 banks in 105 countries, we find that credit information sharing has a negative impact on bank risk. This finding suggests that bank risk is lower in countries with more credit information sharing. Our results rule out the prediction of increasing bank risk, which may result from looser screening requirements and lower post-lending effort in monitoring. Therefore, credit information sharing does not only encourage banks to provide more credits but also induce them to lend safely, promoting bank stability.

In addition, we find that the negative relationship between credit information sharing and bank risk is less pronounced in more transparent information environment. We show that mandatory IFRS adoption mitigates the impact of credit information sharing on bank risk. In addition, the greater extent of business disclosure also moderates the impact of credit information sharing on bank risk. These results suggest that enhancing the transparency of information environment downplays the impact of credit information sharing on bank risk. Thus, credit information sharing has a less beneficial effect on bank risk when the information environment is more transparent.

Moreover, we provide evidence that the negative association between credit information sharing and bank risk is more pronounced in more competitive banking markets. This finding lends support to the argument that banks in competitive banking markets may have less incentive to screen and monitor their borrowers, so adverse selection and moral hazard problems would be more severe than less competitive banking markets. Our findings are robust to various robustness tests, including alternative measures of bank risk, alternative measures of credit information sharing, alternative measures of banking competition, subsample analysis and a potential endogeneity problem.

Figure 3-1: Diagram for Research Question 1

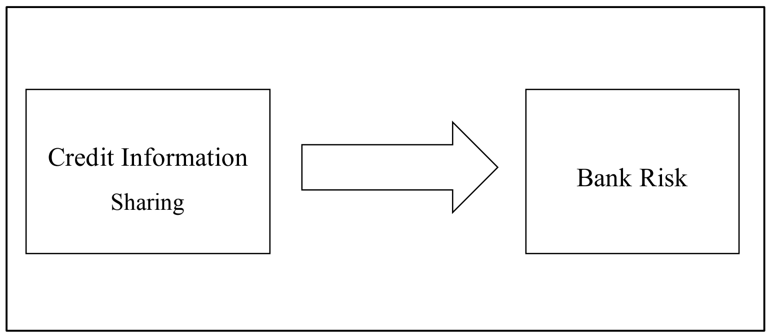

Figure 3-2: Diagram for Research Question 2

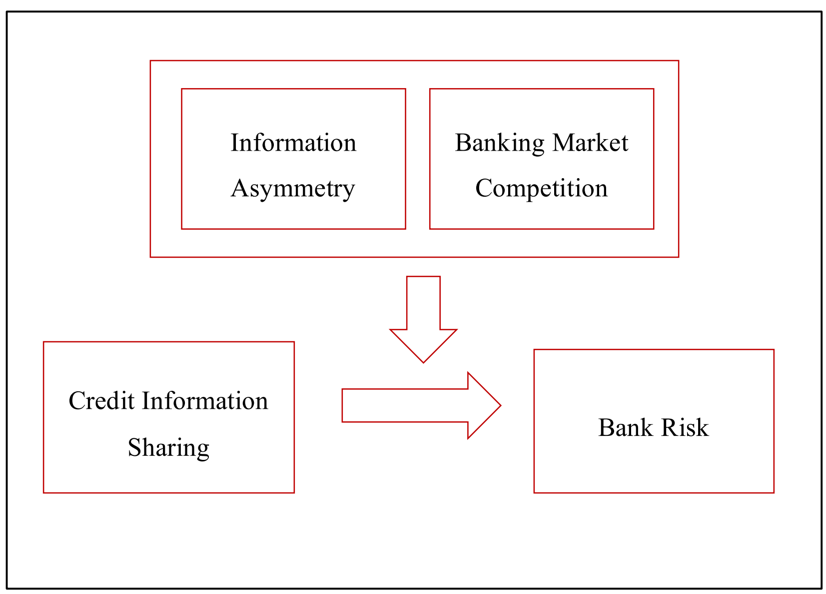

Table 3-1: Summary of Variables, Symbols and Sources

Variables			Definition	Data Sources
Dependent Variables	Z_SCORE	Bank Z-Score	It is inversely related to the probability of a bank's insolvency. The Z-score combines profitability, leverage and the volatility of return into a single ratio showing the number of standard deviations below the mean by which profits would have to fall so as to just deplete equity capital. *Higher (lower) Z_SCORE indicates lower (higher) bank risk*	Bankscope
	Z_SCORE_4WIN	Modified Bank Z-Score	This variable is the modified version of original Z_SCORE. In this version, return on assets (ROAs) from four-period rolling window (t, t-1, t-2 and t-3) are used to calculate Z-Score. *Higher (lower) Z_SCORE_4WIN indicates lower (higher) bank risk*	Bankscope
	Z_SCORE_5WIN	Modified Bank Z-Score	This variable is the modified version of original Z_SCORE. In this version, return on assets (ROAs) from five-period rolling window (t, t-1, t-2, t-3 and t-4) are used to calculate Z-Score. *Higher (lower) Z_SCORE_5WIN indicates lower (higher) bank risk*	Bankscope
	NPL	Nonperforming loans to gross loan (%)	A ratio of nonperforming/defaulting loans (payment of interest and principal past due by 90 days or more) to total gross loans. The loan amount recorded as nonperforming includes the gross value of the loan recorded on the balance sheet, not just the amount that is overdue. *Higher (lower) NPL indicates higher (lower) bank risk*	Bankscope
Explanatory Variables	DEPTH	Depth of credit information sharing index	An index that measures the scope and contents of credit information that being shared. It ranges from zero to six. The value of zero indicates that there is no public credit registry or private credit bureau operating in a country. The value of one is added to the index with each of the following characteristics: • Both positive and negative information are distributed. • Data on households and firms are distributed. • Data from retailers, trade creditors, and/or utility companies as well as financial institutions are distributed. • More than 2 years of data are available.	World Bank's Doing Business database; Djankov *et al.* (2007)

			• Data are collected and distributed on loans with value below 1% of income per capita. • Laws give right to borrowers to inspect their own data. *Higher (lower) DEPTH indicates more (lower) credit information sharing level*	
	PRIV	Private Credit Bureau Coverage (%)	The number of individuals and firms listed by a private credit bureau with information on repayment history, unpaid debts, or credit outstanding from the past five years scaled by the adult population *Higher (lower) PRIV indicates more (lower) credit information sharing level (through private credit bureaus)*	World Bank's Doing Business database; Djankov *et al.* (2007)
	PUB	Public Credit Registry Coverage (%)	The number of individuals and firms listed in a public credit registry with information on repayment history, unpaid debts, or credit outstanding from the past five years scaled by adult population *Higher (lower) PUB indicates more (lower) credit information sharing level (through public credit registries)*	World Bank's Doing Business database; Djankov *et al.* (2007)
	IFRS	International Financial Reporting Standard (IFRS) adoption	A dummy variable whose value is equal to 1 for a country (and year) that adopts IFRS and 0 otherwise. *A value of one (zero) indicates more (less) transparent information environment*	IFRS foundation website, Deloitte and Simon Fraser University in Canada
	BDI	Business Extent of Disclosure Index (BDI)	This index measures the extent to which investors are protected through disclosure of ownership and financial information (World Bank's Doing Business 2016). It ranges from 0 to 10 with higher value indicating more disclosure of ownership and financial information to investors. *Higher (lower) index indicates more (less) transparent information environment*	World Bank's Doing Business
	COMPET1	The conversion of "Lerner Index"	It is calculated as one minus the Lerner index. Lerner index is a measure of market power in the banking market. It is defined as the difference between output prices and marginal costs (relative to prices). An increase in Lerner index indicates a deterioration of the competitive conduct of financial intermediaries. Thus, an increase in one minus the Lerner index indicates more competition. *Higher (lower) value of COMPET1 indicates higher (more) bank competition.*	World Bank's Global Financial Development database; Demirgüç-Kunt and Martínez Pería (2010): Cihak *et al.* (2012); Bankscope

	COMPET2	The conversion of "Three largest bank asset concentration (%)"	It is calculated as one minus the three largest bank asset concentration. The three largest bank asset concentration index is calculated from three largest banks' asset as a share of total commercial banking assets. Total assets include total earning assets, cash and due from banks, foreclosed real estate, fixed assets, goodwill, other intangibles, current tax assets, deferred tax, discontinued operations and other assets. An increase in concentration index indicates less competitive degree in banking market. Thus, an increase in one minus concentration index indicates more competition. *Higher (lower) value of COMPET2 indicates higher (lower) bank competition.*	World Bank's Global Financial Development database; Demirgüç-Kunt and Martínez Pería (2010): Cihak *et al.* (2012); Bankscope
	COMPET3	The conversion of "Five largest bank asset concentration (%)"	It is calculated as one minus the five largest bank asset concentration. The five largest bank asset concentration index is calculated from five largest banks' asset as a share of total commercial banking assets. Total assets include total earning assets, cash and due from banks, foreclosed real estate, fixed assets, goodwill, other intangibles, current tax assets, deferred tax, discontinued operations and other assets. An increase in concentration index indicates less competitive degree in banking market. Thus, an increase in one minus concentration index indicates more competition. *Higher (lower) value of COMPET3 indicates higher (lower) bank competition.*	World Bank's Global Financial Development database; Demirgüç-Kunt and Martínez Pería (2010): Cihak *et al.* (2012); Bankscope
Bank-Specific Control Variables	SIZE	Bank Size	A natural logarithm of a bank's assets (billion US dollars)	Bankscope
	SIZE_SQR	Bank Size Square	A square of a natural logarithm of a bank's total assets (billion US dollars)	Bankscope
	TBTF	Too-Big-Too-Fail	A dummy variable that takes a value of one if the bank's share in the country's total deposits exceeds 10% (Houston *et al.* 2010).	Bankscope
	LOAN	Loans to Deposits (%)	A ratio of total amount of gross loans to total deposit.	Bankscope
	EFFICIENCY	Cost-to-Income Ratio	This is a ratio of the overhead (or cost of running the bank) to operating income (interest and non-interest income), which reflects operations on both on and off balance sheet. This measures the bank's efficiency. Overheads is data2090; Interest income is data2080; Non-interest income is data2085. This is similar to data4029 in BankScope.	Bankscope

Country-Specific Control Variables	GDPG	A growth rate of gross domestic products (GDP)	It captures macroeconomic developments and a proxy for fluctuation in economic activities.	World Development Indicators (WDI)
	INF	Inflation	This is proxied by the consumer price index (CPI). It links to the fluctuation of price movement and higher inflation is associated with high nominal interest, reflecting poor macroeconomic management.	World Development Indicators (WDI)
	CR	Creditor rights index	An aggregate measure of creditor legal protection created based on the methodology proposed by LaPorta *et al.* (1998). The index is ranging from zero to four. The index consists of 4 components: • Restrictions on reorganization: whether there are restrictions imposed, such as creditors' consent or minimum divided, when a debtor files for reorganization. • No automatic stay: whether secured creditors are able to gain possession of assets after the petition for reorganization is approved, that is, whether there is no automatic stay or asset freeze imposed by the court on a creditor's ability to seize collateral. • Secured creditor paid first: whether secured creditors are ranked first in the distribution of proceeds of liquidating a bankrupt firm as opposed to other creditors such as government or workers • No management stay: whether the incumbent management does not stay in control of the firm during the reorganization, in other words, whether an administrator, not the management, is responsible for running the business during the reorganization A value of one is added to the index when a country's laws and regulations provide each of these powers to secured lenders. Higher index indicates that secured lenders are better protected in case a borrower defaults.	LaPorta *et al.* (1998); Djankov *et al.* (2007)
	DEPOSIT_INS	Deposit insurance	A dummy variable that takes a value of one if the country has adopted a deposit insurance regime, and zero otherwise.	Demirgüç-Kunt *et al.* (2008)
	CAPITAL_STR	Capital Stringency index	This is an index measuring the extent of both initial and overall capital stringency. The index ranges from 0 to 10. This index is constructed from following questions: 1. Whether the minimum capital-asset ratio requirement is in line with the Basel Committee on Banking Supervision guidelines	World Bank's *Bank Regulation and Supervision*

			2. Does the minimum ratio varies as a function of an individual bank's credit risk? 3. Does the minimum ratio varies as a function of an individual bank's market risk? 4. Before minimum capital adequacy is determined, which of the following are deducted from the book value of capital: a. Market value of loan losses not realized in accounting books? b. Unrealized losses in securities portfolios? c. Unrealized foreign exchange losses? 5. What fraction of revaluation gains is allowed as part of capital? (1 if the fraction is less than 0.75 and 0 otherwise) 6. Are the sources of funds to be used as capital verified by the regulatory/supervisory authorities? 7. Can the initial disbursement or subsequent injections of capital be done with assets other than cash or government securities? 8. Can initial capital contributions by prospective shareholders be in the form of borrowed funds?	
	ASSET_DIV	Diversification index	The index measures whether there are explicit, verifiable, and quantifiable guideline for asset diversification (e.g. if banks are required to have some minimum diversification of loans among sectors, or if there are sectoral concentration limits) and whether banks are allowed to make loans aboard. Higher index indicates higher asset diversification.	World Bank's *Bank Regulation and Supervision*
	CORRUPTION	Control of Corruption index	This index captures perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests.	World Bank's *Worldwide Governance Indicators* (WGI)
	GOV_EFF	Government Effectiveness index	This index captures perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies.	World Bank's *Worldwide Governance Indicators* (WGI)
	POLITIC	Political Stability index	This index measures perceptions of the likelihood of political instability and/or politically-motivated violence, including terrorism.	World Bank's *Worldwide Governance Indicators* (WGI)
	REG_QUA	Regulatory Quality index	This index captures perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development.	World Bank's *Worldwide Governance Indicators* (WGI)

	RULE_LAW	Rule of Law index	This index captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence.	World Bank's *Worldwide Governance Indicators* (WGI)
	VOICE_ACC	Voice and Accountability index	This index captures perceptions of the extent to which a country's citizens can participate in selecting their government, as well as freedom of expression, freedom of association, and a free media.	World Bank's *Worldwide Governance Indicators* (WGI)
	PUBLIC_OWN	Public Ownership ratio	This ratio is a percentage of banking system's assets in banks that are 50% or more owned by the government.	World Bank's *Bank Regulation and Supervision*
Instrumental Variables	LEGALORIGIN	Legal Origin	A dummy variable whose value is equal to one if a country has English legal origin and otherwise zero.	Djankov *et al.* (2007)
	ETHNIC_FRAC	Ethnic fractionalization	This variable captures the ethnic diversity in a country. It measures probability that two randomly selected people from a given country will not belong to the same ethnolinguistic group.	Easterly (2001)
	LATITUDE	Latitude	This variable measures the geographical latitude of a country. It is calculated as an absolute value of the latitude of the country scaled to take a value between zero and one	La Porta *et al.* (1999); Central Intelligence Agency (CIA)

Table 3-2: Descriptive Statistics

		Variable	Obs.	Mean	Stdev.	Min	Max	P25	P50	P75
Dependent variable		*Z_SCORE*	96,422	3.870	1.520	-6.150	11.700	2.890	3.740	4.760
		Z_SCORE_4WIN	91,572	3.640	1.370	-6.230	10.400	2.790	3.570	4.410
		Z_SCORE_5WIN	86,877	3.500	1.270	-6.150	9.780	2.730	3.460	4.210
		NPL	75,137	0.035	0.061	0.000	1.000	0.004	0.016	0.042
Explanatory variables	CIS	*DEPTH*	96,422	5.040	0.949	0.000	6.000	4.000	5.000	6.000
		PRIV	96,422	0.783	0.353	0.000	1.000	0.612	1.000	1.000
		PUB	96,422	0.091	0.113	0.000	1.000	0.000	0.026	0.237
	ASYM	*IFRS*	96,422	0.290	0.454	0.000	1.000	0.000	0.000	1.000
		BDI	96,422	6.450	1.780	0.000	10.000	6.000	7.000	7.000
	COMPET	*COMPET1*	96,422	0.757	0.090	0.238	0.993	0.680	0.744	0.802
		COMPET2	96,422	0.185	0.137	0.000	0.500	0.058	0.178	0.275
		COMPET3	96,422	0.224	0.143	0.000	0.500	0.051	0.235	0.333
Bank-specific Control		*SIZE*	96,422	5.960	2.030	-5.150	20.400	4.770	5.700	6.920
		SIZE_SQR	96,422	39.700	27.700	0.000	418.000	22.800	32.500	47.800
		TBTF	96,422	0.017	0.128	0.000	1.000	0.000	0.000	0.000
		LOAN	96,422	0.823	0.574	-0.300	9.990	0.608	0.763	0.914
		EFFICIENCY	96,422	0.690	0.293	0.000	9.880	0.568	0.667	0.771
Country-specific Controls		*GDPG*	96,422	0.012	0.028	-0.151	0.185	0.007	0.015	0.024
		INF	96,422	0.031	0.043	-0.251	1.040	0.012	0.020	0.031
		CR	96,422	1.550	0.881	0.000	4.000	1.000	1.000	2.000
		DEPOSIT_INS	96,422	0.965	0.185	0.000	1.000	1.000	1.000	1.000
		CAPITAL_STR	96,422	6.830	1.320	0.000	8.000	6.000	7.000	8.000
		ASSET_DIV	96,422	0.340	0.501	0.000	2.000	0.000	0.000	1.000
		CORRUPTION	96,422	1.030	0.867	-1.440	2.550	1.260	1.320	1.510
		GOV_EFF	96,422	1.200	0.746	-1.570	2.370	1.450	1.510	1.600
		POLITIC	96,422	0.372	0.607	-2.810	1.590	0.374	0.488	0.635
		REG_QUA	96,422	1.140	0.679	-1.640	1.990	1.210	1.440	1.540
		RULE_LAW	96,422	1.170	0.848	-1.790	2.000	1.350	1.580	1.610
		VOICE_ACCT	96,422	0.900	0.688	-1.770	1.770	1.080	1.110	1.280
		PUBLIC_OWN	93,059	0.106	0.170	0.000	0.900	0.000	0.000	0.203
Instrumental Variables		*LEGALORIGIN*	96,422	0.576	0.494	0.000	1.000	0.000	1.000	1.000
		ETHNIC_FRAC	87,300	0.378	0.219	0.000	0.930	0.130	0.500	0.500
		LATITUDE	95,558	0.703	0.082	0.295	0.835	0.691	0.691	0.768

This table presents descriptive statistics of variables used in the analysis. Each of *Z_SCORE, Z_SCORE_3SD* and *Z_SCORE_4SD* is an indicator of bank stability. For *Z_SCORE_4WIN,* ROA from four-period rolling window (t, t-1, t-2 and t-3) are used to calculate the standard deviation of ROA in the Z-Score formula, while, for *Z_SCORE_5WIN,* ROA from five-period rolling window (t, t-1, t-2, t-3 and t-4) are used to calculate the standard deviation of ROA in the Z-Score formula. *NPL* is the ratio of non-performing loans to total gross loans; *CIS* represents credit information sharing measures; *DEPTH* is depth of credit information sharing index; *PRIV* is private credit bureau coverage (% of adult population); *PUB* is public credit registry coverage (% of adult population); *ASYM* represents information environment proxies; *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *BDI* is a business extent of disclosure index; *COMPET* represents competition measures; *COMPET1* is the 1st competition measure converted from one minus Lerner Index; *COMPET2* is the 2nd competition measure converted from concentration index calculated from the fraction of assets held by the 3 largest banks in each country; *COMPET3* is the 3rd competition measure converted from concentration index calculated from the fraction of assets held by the 5 largest banks in each country; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *SIZE_SQR* is a square of a natural logarithm of total asset; *TBTF* is too-big-too-fail dummy whose value is equal to one if the bank's share in the country's total deposits exceeds 10% and zero otherwise; *LOAN* is a ratio of total gross loans to total assets; *EFFICIENCY* is a ratio of total cost to total income; *GDPG* is real GDP growth; *INF* is inflation; *CR* is creditor rights index; *DEPOSIT_INS* is a dummy for deposit insurance taking a value of one if the country has adopted a deposit insurance regime, and zero otherwise; *CAPITAL_STR* is capital stringency index measuring the extent of both initial and overall capital stringency; *ASSET_DIV* is asset diversification index measuring the extent of bank asset diversification; *CORRUPTION* is a control of corruption index; *GOV_EFF* is a government effectiveness index; *POLITIC* is a political stability index; *REG_QUA* is a regulatory quality index; *RULE_LAW* is a rule of law index; *VOICE_ACC* is a voice and accountatbility index; *PUBLIC_OWN* is a percentage of total assets in the banking system owned by the government; *LEGALORIGIN* is dummy variable whose value is equal to one if a country has English legal origin and otherwise zero; *ETHNIC_FRAC* is an ethnic fractionalization which captures the ethnic diversity in a country; *LATITUDE* is a latitude which measures the geographical latitude of a country. Further detail of all variables are presented in Table 3-1 in this chapter. Obs is observation. Stdev is for standard deviation. Min is minimum. Max is maximum. P25 is 25th percentile of the sample. P50 is 50th percentile (or median) of the sample. P75 is 75th percentile of the sample

Table 3-3: Mean Value of Bank Risk, Depth of Credit Information Sharing and Competition Measures – By Year

Year	Obs.	*Z_SCORE*	*NPL*	*DEPTH*	*COMPET1*	*COMPET2*	*COMPET3*
2005	9,654	4.0767	0.0189	5.0367	0.7414	0.1240	0.1474
2006	9,490	4.1049	0.0180	5.0392	0.7605	0.1194	0.1421
2007	11,022	4.0157	0.0227	5.0013	0.7886	0.1410	0.1729
2008	10,819	3.6853	0.0275	4.9804	0.8091	0.1460	0.1766
2009	11,086	3.5108	0.0402	5.0391	0.7650	0.1740	0.2159
2010	11,442	3.6010	0.0466	5.0274	0.7375	0.2322	0.2673
2011	11,286	3.8057	0.0471	5.0596	0.7426	0.2372	0.2806
2012	11,248	3.9929	0.0442	5.0902	0.7430	0.2374	0.2897
2013	10,375	4.1304	0.0392	5.1229	0.7223	0.2514	0.2993
2005-2013	96,422	3.8700	0.0348	5.0400	0.7570	0.1850	0.2240

The table shows the mean of our main variables by year. *Z_SCORE* is an indicator of bank risk. *NPL* is the ratio of non-performing loans to total gross loans. *DEPTH* is a depth of credit information sharing index. *COMPET1, COMPET2* and *COMPET3* are indicators of bank competition and they are converted by subtracting one from each of *LERNER, CCT3* and *CCT5,* respectively. *LERNER* is Lerner index (higher index indicates lower competition). *CCT3* is the fraction of assets held by the 3 largest banks in each country (higher index indicates lower competition). *CCT5* is the fraction of assets held by the 5 largest banks in each country (higher index indicates lower competition).

Table 3-4: Pearson Correlation Matrix

Variable	***Z_SCORE***	***Z_SCORE_4WIN***	***Z_SCORE_5WIN***	***NPL***	***DEPTH***	***PRIV***	***PUB***	***IFRS***	***BDI***	***COMPET1***
Z_SCORE	1.000									
Z_SCORE_4WIN	0.897	1.000								
Z_SCORE_5WIN	0.823	0.929	1.000							
NPL	-0.212	-0.232	-0.242	1.000						
DEPTH	0.093	0.092	0.095	-0.267	1.000					
PRIV	0.045	0.038	0.033	-0.269	0.758	1.000				
PUB	0.008	0.008	0.005	0.304	-0.311	-0.486	1.000			
IFRS	0.100	0.113	0.125	0.299	-0.259	-0.357	0.662	1.000		
BDI	-0.095	-0.104	-0.114	-0.087	0.136	0.330	-0.195	-0.285	1.000	
COMPET1	0.107	0.138	0.166	-0.125	-0.191	-0.325	0.285	0.379	-0.458	1.000
COMPET2	0.002	-0.006	-0.008	0.347	-0.587	-0.595	0.415	0.493	-0.383	0.199
COMPET3	0.021	0.014	0.012	0.339	-0.498	-0.516	0.400	0.509	-0.308	0.203
SIZE	0.147	0.163	0.177	0.186	-0.152	-0.206	0.371	0.436	-0.119	0.159
SIZE_SQR	0.147	0.163	0.177	0.186	-0.152	-0.206	0.371	0.436	-0.119	0.159
TBTF	-0.058	-0.061	-0.063	0.052	-0.130	-0.146	0.076	0.029	0.003	-0.056
LOAN	0.008	0.015	0.018	0.028	-0.141	-0.018	-0.039	-0.030	0.034	0.076
EFFICIENCY	-0.226	-0.232	-0.231	0.149	0.095	0.063	-0.107	-0.063	-0.091	0.090
GDPG	0.042	0.030	0.021	-0.073	-0.164	-0.261	0.095	-0.002	-0.172	-0.001
INF	-0.079	-0.076	-0.081	-0.191	-0.282	-0.167	-0.096	-0.188	0.061	0.164
CR	0.071	0.078	0.084	0.243	-0.184	-0.401	0.404	0.602	-0.480	0.398
DEPOSIT_INS	0.059	0.063	0.066	-0.073	0.265	0.281	-0.169	0.020	0.026	0.054
CAPITAL_STR	-0.038	-0.049	-0.056	0.015	0.466	0.700	-0.391	-0.355	0.350	-0.441
ASSET_DIV	0.036	0.038	0.044	0.216	-0.415	-0.605	0.374	0.380	-0.380	0.406
CORRUPTION	0.226	0.245	0.259	-0.312	0.372	0.257	-0.027	0.288	-0.122	0.280
GOV_EFF	0.156	0.178	0.197	-0.389	0.429	0.380	-0.239	0.014	0.007	0.230
POLITIC	0.163	0.158	0.155	0.081	0.274	0.133	0.087	0.359	-0.235	0.015
REG_QUA	0.176	0.201	0.221	-0.401	0.515	0.449	-0.244	0.048	-0.017	0.217
RULE_LAW	0.132	0.144	0.166	-0.115	0.482	0.373	-0.149	0.174	-0.157	0.115
VOICE_ACCT	0.183	0.196	0.214	-0.177	0.334	0.234	0.017	0.333	-0.138	0.203
PUBLIC_OWN	0.052	0.061	0.071	0.297	-0.510	-0.722	0.540	0.534	-0.588	0.589
LEGALORIGIN	-0.062	-0.069	-0.074	-0.311	0.555	0.726	-0.670	-0.617	0.523	-0.467
ETHNIC_FRAC	-0.125	-0.132	-0.138	-0.253	0.072	0.318	-0.587	-0.738	0.370	-0.379
LATITUDE	0.104	0.121	0.139	0.130	-0.245	-0.335	0.223	0.553	-0.327	0.504

This table shows Pearson correlations between variables. Each of *Z_SCORE, Z_SCORE_3SD* and *Z_SCORE_4SD* is an indicator of bank stability. For *Z_SCORE_4WIN,* ROA from four-period rolling window (t, t-1, t-2 and t-3) are used to calculate the standard deviation of ROA in the Z-Score formula, while, for *Z_SCORE_5WIN,* ROA from five-period rolling window (t, t-1, t-2, t-3 and t-4) are used to calculate the standard deviation of ROA in the Z-Score formula. *NPL* is the ratio of non-performing loans to total gross loans. *DEPTH* is depth of credit information sharing index; *PRIV* is private credit bureau coverage (% of adult population); *PUB* is public credit registry coverage (% of adult population); *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *BDI* is a business extent of disclosure index; *COMPET1* is the 1st competition measure converted from one minus Lerner Index; *COMPET2* is the 2nd competition measure converted from concentration index calculated from the fraction of assets held by the 3 largest banks in each country; *COMPET3* is the 3rd competition measure converted from concentration index calculated from the fraction of assets held by the 5 largest banks in each country; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *SIZE_SQR* is a square of a natural logarithm of total asset; *TBTF* is too-big-too-fail dummy whose value is equal to one if the bank's share in the country's total deposits exceeds 10% and zero otherwise; *LOAN* is a ratio of total gross loans to total assets; *EFFICIENCY* is a ratio of total cost to total income; *GDPG* is real GDP growth; *INF* is inflation; *CR* is creditor rights index; *DEPOSIT_INS* is a dummy for deposit insurance taking a value of one if the country has adopted a deposit insurance regime, and zero otherwise; *CAPITAL_STR* is capital stringency index measuring the extent of both initial and overall capital stringency; *ASSET_DIV* is asset diversification index measuring the extent of bank asset diversification; *CORRUPTION* is a control of corruption index; *GOV_EFF* is a government effectiveness index; *POLITIC* is a political stability index; *REG_QUA* is a regulatory quality index; *RULE_LAW* is a rule of law index; *VOICE_ACC* is a voice and accountability index; *PUBLIC_OWN* is a percentage of total assets in the banking system owned by the government; *LEGALORIGIN* is dummy variable whose value is equal to one if a country has English legal origin and otherwise zero; *ETHNIC_FRAC* is an ethnic fractionalization which captures the ethnic diversity in a country; *LATITUDE* is a latitude which measures the geographical latitude of a country. Further detail of all variables are presented in Table 3-1 in this chapter.

Table 3-5: Pearson Correlation Matrix (Continued)

Variable	*COMPET2*	*COMPET3*	*SIZE*	*SIZE_SQR*	*TBTF*	*LOAN*	*EFFICIENCY*	*GDPG*	*INF*	*CR*
COMPET2	1.000									
COMPET3	0.939	1.000								
SIZE	0.304	0.321	1.000							
SIZE_SQR	0.304	0.321	1.000	1.000						
TBTF	0.049	-0.003	0.066	0.066	1.000					
LOAN	0.002	-0.005	0.017	0.017	0.023	1.000				
EFFICIENCY	0.016	0.037	-0.203	-0.203	-0.072	-0.039	1.000			
GDPG	0.183	0.132	-0.005	-0.004	0.049	-0.071	-0.101	1.000		
INF	-0.028	-0.083	-0.138	-0.137	0.064	0.102	-0.076	0.353	1.000	
CR	0.445	0.466	0.234	0.234	0.061	-0.071	0.010	0.189	-0.012	1.000
DEPOSIT_INS	-0.140	-0.055	-0.079	-0.079	-0.174	0.084	0.120	-0.173	-0.208	-0.090
CAPITAL_STR	-0.370	-0.303	-0.171	-0.171	-0.143	0.010	0.095	-0.411	-0.330	-0.486
ASSET_DIV	0.521	0.482	0.210	0.210	0.098	-0.045	-0.009	0.192	0.053	0.427
CORRUPTION	-0.111	-0.075	0.187	0.187	-0.100	-0.079	-0.034	-0.084	-0.290	0.052
GOV_EFF	-0.363	-0.328	0.029	0.029	-0.112	-0.003	-0.034	-0.112	-0.142	-0.131
POLITIC	0.186	0.219	0.199	0.199	-0.069	-0.121	0.025	-0.130	-0.557	0.162
REG_QUA	-0.399	-0.359	0.034	0.034	-0.114	-0.034	-0.030	-0.058	-0.127	-0.058
RULE_LAW	-0.102	-0.052	0.134	0.134	-0.112	-0.096	0.036	-0.216	-0.483	0.058
VOICE_ACCT	-0.033	0.010	0.211	0.211	-0.112	-0.087	-0.017	-0.083	-0.384	0.046
PUBLIC_OWN	0.645	0.610	0.270	0.270	0.087	0.004	0.031	0.285	0.107	0.664
LEGALORIGIN	-0.655	-0.617	-0.292	-0.292	-0.080	-0.029	-0.002	-0.189	0.050	-0.584
ETHNIC_FRAC	-0.419	-0.476	-0.301	-0.301	0.016	0.039	-0.028	-0.023	0.316	-0.611
LATITUDE	0.500	0.566	0.215	0.215	-0.067	0.072	0.128	-0.034	-0.215	0.475

This table shows Pearson correlations between variables. Each of *Z_SCORE, Z_SCORE_3SD* and *Z_SCORE_4SD* is an indicator of bank stability. For *Z_SCORE_4WIN,* ROA from four-period rolling window (t, t-1, t-2 and t-3) are used to calculate the standard deviation of ROA in the Z-Score formula, while, for *Z_SCORE_5WIN,* ROA from five-period rolling window (t, t-1, t-2, t-3 and t-4) are used to calculate the standard deviation of ROA in the Z-Score formula. *NPL* is the ratio of non-performing loans to total gross loans. *DEPTH* is depth of credit information sharing index; *PRIV* is private credit bureau coverage (% of adult population); *PUB* is public credit registry coverage (% of adult population); *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *BDI* is a business extent of disclosure index; *COMPET1* is the 1st competition measure converted from one minus Lerner Index; *COMPET2* is the 2nd competition measure converted from concentration index calculated from the fraction of assets held by the 3 largest banks in each country; *COMPET3* is the 3rd competition measure converted from concentration index calculated from the fraction of assets held by the 5 largest banks in each country; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *SIZE_SQR* is a square of a natural logarithm of total asset; *TBTF* is too-big-too-fail dummy whose value is equal to one if the bank's share in the country's total deposits exceeds 10% and zero otherwise; *LOAN* is a ratio of total gross loans to total assets; *EFFICIENCY* is a ratio of total cost to total income; *GDPG* is real GDP growth; *INF* is inflation; *CR* is creditor rights index; *DEPOSIT_INS* is a dummy for deposit insurance taking a value of one if the country has adopted a deposit insurance regime, and zero otherwise; *CAPITAL_STR* is capital stringency index measuring the extent of both initial and overall capital stringency; *ASSET_DIV* is asset diversification index measuring the extent of bank asset diversification; *CORRUPTION* is a control of corruption index; *GOV_EFF* is a government effectiveness index; *POLITIC* is a political stability index; *REG_QUA* is a regulatory quality index; *RULE LAW* is a rule of law index; *VOICE ACC* is a voice and accountability index; *PUBLIC_OWN* is a percentage of total assets in the banking system owned by the government; *LEGALORIGIN* is dummy variable whose value is equal to one if a country has English legal origin and otherwise zero; *ETHNIC_FRAC* is an ethnic fractionalization which captures the ethnic diversity in a country; *LATITUDE* is a latitude which measures the geographical latitude of a country. Further detail of all variables are presented in Table 3-1 in this chapter.

Table 3-6: Pearson Correlation Matrix (Continued)

Variable	***DEPOSIT_INS***	***CAPITAL_STR***	***ASSET_DIV***	***CORRUPTION***	***GOV_EFF***	***POLITIC***	***REG_QUA***	***RULE_LAW***	***VOICE_ACCT***	***PUBLIC_OWN***	***LEGALORIGIN***	***ETHNIC_FRAC***	***LATITUDE***
DEPOSIT_INS	1.000												
CAPITAL_STR	0.250	1.000											
ASSET_DIV	-0.081	-0.557	1.000										
CORRUPTION	0.237	0.015	0.003	1.000									
GOV_EFF	0.248	0.067	-0.208	0.777	1.000								
POLITIC	0.197	0.124	0.055	0.649	0.430	1.000							
REG_QUA	0.253	0.101	-0.215	0.794	0.881	0.397	1.000						
RULE_LAW	0.241	0.255	-0.117	0.733	0.732	0.675	0.688	1.000					
VOICE_ACCT	0.262	0.086	0.017	0.886	0.696	0.603	0.697	0.819	1.000				
PUBLIC_OWN	-0.167	-0.671	0.679	-0.078	-0.329	0.005	-0.285	-0.151	-0.060	1.000			
LEGALORIGIN	0.092	0.640	-0.632	0.022	0.246	-0.173	0.279	0.141	-0.006	-0.827	1.000		
ETHNIC_FRAC	-0.113	0.369	-0.377	-0.312	-0.015	-0.452	-0.065	-0.203	-0.308	-0.649	0.756	1.000	
LATITUDE	0.301	-0.278	0.391	0.316	0.127	0.357	0.117	0.229	0.354	0.502	-0.615	-0.688	1.000

This table shows Pearson correlations between variables. Each of *Z_SCORE, Z_SCORE_3SD* and *Z_SCORE_4SD* is an indicator of bank stability. For *Z_SCORE_4WIN,* ROA from four-period rolling window (t, t-1, t-2 and t-3) are used to calculate the standard deviation of ROA in the Z-Score formula, while, for *Z_SCORE_5WIN,* ROA from five-period rolling window (t, t-1, t-2, t-3 and t-4) are used to calculate the standard deviation of ROA in the Z-Score formula. *NPL* is the ratio of non-performing loans to total gross loans. *DEPTH* is depth of credit information sharing index; *PRIV* is private credit bureau coverage (% of adult population); *PUB* is public credit registry coverage (% of adult population); *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *BDI* is a business extent of disclosure index; *COMPET1* is the 1st competition measure converted from one minus Lerner Index; *COMPET2* is the 2nd competition measure converted from concentration index calculated from the fraction of assets held by the 3 largest banks in each country; *COMPET3* is the 3rd competition measure converted from concentration index calculated from the fraction of assets held by the 5 largest banks in each country; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *SIZE_SQR* is a square of a natural logarithm of total asset; *TBTF* is too-big-too-fail dummy whose value is equal to one if the bank's share in the country's total deposits exceeds 10% and zero otherwise; *LOAN* is a ratio of total gross loans to total assets; *EFFICIENCY* is a ratio of total cost to total income; *GDPG* is real GDP growth; *INF* is inflation; *CR* is creditor rights index; *DEPOSIT_INS* is a dummy for deposit insurance taking a value of one if the country has adopted a deposit insurance regime, and zero otherwise; *CAPITAL_STR* is capital stringency index measuring the extent of both initial and overall capital stringency; *ASSET_DIV* is asset diversification index measuring the extent of bank asset diversification; *CORRUPTION* is a control of corruption index; *GOV_EFF* is a government effectiveness index; *POLITIC* is a political stability index; *REG_QUA* is a regulatory quality index; *RULE_LAW* is a rule of law index; *VOICE_ACC* is a voice and accountability index; *PUBLIC_OWN* is a percentage of total assets in the banking system owned by the government; *LEGALORIGIN* is dummy variable whose value is equal to one if a country has English legal origin and otherwise zero; *ETHNIC_FRAC* is an ethnic fractionalization which captures the ethnic diversity in a country; *LATITUDE* is a latitude which measures the geographical latitude of a country. Further detail of all variables are presented in Table 3-1 in this chapter.

Table 3-7: Model Selection and Diagnostic Tests

Panel A: Poolability Test

F(15557, 80852)	6.55
F(15557, 80852) P-value	0.00

The test of poolability is performed to determine the presence of individual effects, α_i in the regression model. H_0: α_i=0 for i = 1, 2, 3…., N. The rejection of the null hypothesis indicates that the individual effects exist and the OLS estimates suffer from the problem of omitted variables.

Panel B: Hausman Test

Chi-sq(12)	1191.52
Chi-sq(12) P-value	0.00

The Hausman test is performed to choose between the fixed effect model and the random effect model. H_0: difference in coefficients not systemic. The rejection of the null hypothesis indicates that the fix effect regression model is preferable to the random effect.

Panel C: Modified Wald Test for Groupwise Heteroskedasticity in Fixed Effect Regression Model

Chi-sq(15558)	383.38
Chi-sq(15558) P-value	0.00

The modified Wald test is performed to test for the presence of groupwise heteroskedasticity in the residuals. H_0: $\sigma_i^2 = \sigma^2$ for i = 1, 2, 3…., Ng, where Ng is the number of cross-sectional units. The rejection of the null hypothesis indicates that there exist the groupwise geteroskedasticity.

Panel D: Wooldridge Test for Autocorrelation in Panel Data

F(1, 13149)	11066.864
F(1, 13149) P-value	0.00

The Wooldridge test is performed to test for the presence of serial correlation. H_0: no first-order autocorrelation. The rejection of the null hypothesis indicates that data does not have first-order autocorrelation.

Table 3-8: The Impact of Credit Information Sharing on Bank Risk

Variable	***Z_SCORE***
	(1)
DEPTH	0.117**
	(2.42)
SIZE	0.196**
	(2.37)
SIZE_SQR	-0.013**
	(-2.48)
TBTF	-0.579***
	(-3.62)
LOAN	0.029
	(0.59)
EFFICIENCY	-1.204***
	(-5.35)
GDPG	0.831
	(0.64)
INF	-2.246**
	(-2.19)
CR	0.161
	(1.35)
DEPOSIT_INS	0.115
	(0.88)
CAPITAL_STR	0.094**
	(2.24)
ASSET_DIV	0.338***
	(2.69)
Constant	1.828*
	(1.77)
R-squared	0.235
Bank Fixed Effects	Yes
Time Dummies	Yes
Observations	96,422

The table presents the regression results for the impact of credit information sharing on bank risk. The dependent variable is bank risk measured by *Z_SCORE*. *Z_SCORE* is an indicator of bank stability. *DEPTH* is depth of credit information sharing index; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *SIZE_SQR* is bank size squared; *TBTF* is too-big-too-fail dummy whose value is equal to one if the bank's share in the country's total deposits exceeds 10% and zero otherwise; *LOAN* is a ratio of total gross loans to total assets; *EFFICIENCY* is a ratio of total cost to total income; *GDPG* is real GDP growth; INF is inflation; *CR* is creditor rights index; *DEPOSIT_INS* is a dummy for deposit insurance taking a value of one if the country has adopted a deposit insurance regime, and zero otherwise; *CAPITAL_STR* is capital stringency index measuring the extent of both initial and overall capital stringency; *ASSET_DIV* is asset diversification index measuring the extent of bank asset diversification. Further detail of all variables are presented in Table 3-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 3-9: The Impact of Credit Information Sharing on Bank Risk - The Role of Information Asymmetry

Variable	*Z_SCORE*				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
DEPTH	0.117**	0.126**	0.495**	0.123**	0.518***
	(2.42)	(2.18)	(2.16)	(2.58)	(3.45)
IFRS		0.079**	0.552***		
		(2.50)	(3.03)		
IFRS * DEPTH			-0.408***		
			(-2.98)		
BDI				0.088***	0.250**
				(3.32)	(2.51)
BDI * DEPTH					-0.069**
					(-2.46)
SIZE	0.196**	0.191**	0.192**	0.169**	0.174**
	(2.37)	(2.39)	(2.51)	(2.15)	(2.34)
SIZE_SQR	-0.013**	-0.013**	-0.013***	-0.011**	-0.012**
	(-2.48)	(-2.51)	(-2.65)	(-2.18)	(-2.48)
TBTF	-0.579***	-0.565***	-0.596***	-0.549***	-0.458***
	(-3.62)	(-3.61)	(-4.17)	(-3.85)	(-3.65)
LOAN	0.029	0.027	0.023	0.033	0.021
	(0.59)	(0.54)	(0.46)	(0.69)	(0.42)
EFFICIENCY	-1.204***	-1.204***	-1.213***	-1.222***	-1.228***
	(-5.35)	(-5.34)	(-5.47)	(-5.63)	(-5.71)
GDPG	0.831	1.094	0.647	0.951	0.642
	(0.64)	(0.74)	(0.45)	(0.72)	(0.50)
INF	-2.246**	-2.207**	-2.313**	-1.943**	-1.652**
	(-2.19)	(-2.08)	(-2.34)	(-2.17)	(-2.18)
CR	0.161	0.142	0.064	0.124	0.137*
	(1.35)	(1.36)	(0.73)	(1.26)	(1.67)
DEPOSIT_INS	0.115	0.097	0.224*	0.079	0.164
	(0.88)	(0.71)	(1.74)	(0.56)	(1.31)
CAPITAL_STR	0.094**	0.097**	0.101**	0.106**	0.122***
	(2.24)	(2.22)	(2.26)	(2.54)	(2.74)
ASSET_DIV	0.338***	0.330***	0.294***	0.284**	0.220**
	(2.69)	(2.63)	(2.78)	(2.49)	(2.43)
Constant	1.828*	1.881*	2.769***	2.302***	0.333
	(1.77)	(1.92)	(3.83)	(2.67)	(0.28)
R-squared	0.235	0.235	0.242	0.244	0.250
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes
Observations	96,422	96,422	96,422	96,422	96,422

The table presents the regression results for the impact of information asymmetry on the relationship between credit information sharing and bank risk. The dependent variable is bank risk measured by *Z_SCORE*. *Z_SCORE* is an indicator of bank stability. *DEPTH* is depth of credit information sharing index; *IFRS* and *BDI* are proxies of information environment; *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *BDI* is a business extent of disclosure index; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *SIZE_SQR* is bank size squared; *TBTF* is too-big-too-fail dummy whose value is equal to one if the bank's share in the country's total deposits exceeds 10% and zero otherwise; *LOAN* is a ratio of total gross loans to total assets; *EFFICIENCY* is a ratio of total cost to total income; *GDPG* is real GDP growth; INF is inflation; *CR* is creditor rights index; *DEPOSIT_INS* is a dummy for deposit insurance taking a value of one if the country has adopted a deposit insurance regime, and zero otherwise; *CAPITAL_STR* is capital stringency index measuring the extent of both initial and overall capital stringency; *ASSET_DIV* is asset diversification index measuring the extent of bank asset diversification. Further detail of all variables are presented in Table 3-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 3-10: The Impact of Credit Information Sharing on Bank Risk - The Role of Banking Competition

Variable	*Z_SCORE*		
	(1)	**(2)**	**(3)**
DEPTH	0.117**	0.097***	0.0904***
	(2.42)	(2.74)	(3.36)
COMPET1		-2.389***	-4.675***
		(-4.12)	(-2.79)
COMPET1 * DEPTH			1.370***
			(3.57)
SIZE	0.196**	0.171**	0.150**
	(2.37)	(2.36)	(2.10)
SIZE_SQR	-0.013**	-0.012**	-0.011**
	(-2.48)	(-2.45)	(-2.21)
TBTF	-0.579***	-0.410***	-0.399***
	(-3.62)	(-3.37)	(-3.49)
LOAN	0.029	0.005	0.016
	(0.59)	(0.11)	(0.33)
EFFICIENCY	-1.204***	-1.269***	-1.262***
	(-5.35)	(-6.47)	(-6.29)
GDPG	0.831	2.144**	2.445**
	(0.64)	(1.99)	(2.45)
INF	-2.246**	-2.778***	-2.754***
	(-2.19)	(-3.12)	(-3.21)
CR	0.161	0.085	0.031
	(1.35)	(1.00)	(0.43)
DEPOSIT_INS	0.115	0.049	0.102
	(0.88)	(0.42)	(0.98)
CAPITAL_STR	0.094**	0.097**	0.095**
	(2.24)	(2.28)	(2.34)
ASSET_DIV	0.338***	0.203**	0.208**
	(2.69)	(2.09)	(2.23)
Constant	1.828*	0.411	5.690***
	(1.77)	(0.40)	(5.09)
R-squared	0.235	0.247	0.253
Bank Fixed Effects	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes
Observations	96,422	96,422	96,422

The table presents the regression results for the impact of banking competition on the relationship between credit information sharing and bank risk. The dependent variable is bank risk measured by *Z_SCORE*. *Z_SCORE* is an indicator of bank stability. *DEPTH* is depth of credit information sharing index; *COMPET1* is a measure of banking competition converted from Lerner Index; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *SIZE_SQR* is bank size squared; *TBTF* is too-big-too-fail dummy whose value is equal to one if the bank's share in the country's total deposits exceeds 10% and zero otherwise; *LOAN* is a ratio of total gross loans to total assets; *EFFICIENCY* is a ratio of total cost to total income; *GDPG* is real GDP growth; INF is inflation; *CR* is creditor rights index; *DEPOSIT_INS* is a dummy for deposit insurance taking a value of one if the country has adopted a deposit insurance regime, and zero otherwise; *CAPITAL_STR* is capital stringency index measuring the extent of both initial and overall capital stringency; *ASSET_DIV* is asset diversification index measuring the extent of bank asset diversification. Further detail of all variables are presented in Table 3-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

* indicates significance at the 10% level

** indicates significance at the 5% level

*** indicates significance at the 1% level

Table 3-11: Estimation Results with Alternative Measure of Bank Risk - Z_SCORE_4WIN

Variable	Z_SCORE_4WIN						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DEPTH	0.109**	0.121**	0.39**	0.114**	0.518***	0.090**	0.099***
	(2.11)	(2.06)	(2.02)	(2.25)	(3.53)	(2.43)	(4.37)
IFRS		0.099**	0.599***				
		(2.61)	(3.30)				
IFRS * DEPTH			-0.337***				
			(-3.28)				
BDI				0.084***	0.263**		
				(3.36)	(2.61)		
BDI * DEPTH					-0.071**		
					(-2.47)		
COMPET1						-2.510***	-5.213***
						(-4.89)	(-3.50)
COMPET1 * DEPTH							1.489***
							(4.57)
SIZE	0.205**	0.198**	0.197**	0.176**	0.181**	0.175**	0.151**
	(2.37)	(2.38)	(2.49)	(2.16)	(2.36)	(2.34)	(2.02)
SIZE_SQR	-0.014**	-0.013**	-0.013**	-0.011**	-0.012**	-0.012**	-0.011**
	(-2.43)	(-2.46)	(-2.58)	(-2.13)	(-2.44)	(-2.39)	(-2.11)
TBTF	-0.591***	-0.573***	-0.616***	-0.559***	-0.465***	-0.403***	-0.390***
	(-3.74)	(-3.72)	(-4.50)	(-3.92)	(-3.69)	(-3.44)	(-3.57)
LOAN	0.044	0.042	0.038	0.047	0.034	0.016	0.026
	(0.90)	(0.83)	(0.75)	(0.97)	(0.69)	(0.33)	(0.55)
EFFICIENCY	-1.170***	-1.171***	-1.180***	-1.189***	-1.196***	-1.240***	-1.229***
	(-5.59)	(-5.58)	(-5.76)	(-5.92)	(-6.04)	(-7.01)	(-6.74)
GDPG	0.046	0.387	0.150	0.142	-0.000	1.477	1.672*
	(0.03)	(0.24)	(0.10)	(0.10)	(-0.00)	(1.35)	(1.70)
INF	-1.827	-1.776	-1.892*	-1.513	-1.215	-2.416**	-2.435***
	(-1.63)	(-1.52)	(-1.77)	(-1.52)	(-1.44)	(-2.55)	(-2.65)
CR	0.151	0.127	0.049	0.115	0.131*	0.070	0.009
	(1.35)	(1.31)	(0.59)	(1.24)	(1.70)	(0.90)	(0.14)
DEPOSIT_INS	0.087	0.065	0.220	0.059	0.150	0.018	0.075
	(0.61)	(0.45)	(1.59)	(0.39)	(1.15)	(0.14)	(0.68)
CAPITAL_STR	0.088**	0.091**	0.100**	0.101**	0.119***	0.094**	0.090**
	(2.08)	(2.05)	(2.20)	(2.43)	(2.64)	(2.27)	(2.30)
ASSET_DIV	0.317**	0.306**	0.264**	0.266**	0.196**	0.180*	0.189**
	(2.59)	(2.47)	(2.55)	(2.33)	(2.17)	(1.93)	(2.16)
Constant	1.589	1.657*	2.619***	2.043**	0.033	0.120	5.901***
	(1.55)	(1.72)	(3.61)	(2.36)	(0.03)	(0.12)	(5.77)
R-squared	0.242	0.243	0.251	0.252	0.260	0.259	0.266
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	91,572	91,572	91,572	91,572	91,572	91,572	91,572

The table presents the regression results for the impact of credit information sharing on bank risk. The dependent variable is bank risk measured by *Z_SCORE_4WIN*. For all these regressions, ROA from four-period rolling window (t, t-1, t-2 and t-3) are used to calculate the standard deviation of ROA in the Z-Score formula. *Z_SCORE_4WIN* is an indicator of bank stability. *DEPTH* is depth of credit information sharing index; *IFRS* and *BDI* are proxies of information environment; *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *BDI* is a business extent of disclosure index; *COMPET1* is a measure of banking competition converted from Lerner Index; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *SIZE_SQR* is bank size squared; *TBTF* is too-big-too-fail dummy whose value is equal to one if the bank's share in the country's total deposits exceeds 10% and zero otherwise; *LOAN* is a ratio of total gross loans to total assets; *EFFICIENCY* is a ratio of total cost to total income; *GDPG* is real GDP growth; *INF* is inflation; *CR* is creditor rights index; *DEPOSIT_INS* is a dummy for deposit insurance taking a value of one if the country has adopted a deposit insurance regime, and zero otherwise; *CAPITAL_STR* is capital stringency index measuring the extent of both initial and overall capital stringency; *ASSET_DIV* is asset diversification index measuring the extent of bank asset diversification. Further detail of all variables are presented in Table 3-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 3-12: Estimation Results with Alternative Measure of Bank Risk - Z_SCORE_5WIN

Variable	*Z_SCORE_5WIN*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DEPTH	0.103*	0.117*	0.405*	0.107*	0.507***	0.08**	0.086***
	(1.87)	(1.91)	(1.97)	(1.97)	(3.57)	(2.14)	(-4.83)
IFRS		0.121**	0.689***				
		(2.72)	(3.55)				
IFRS * DEPTH			-0.357***				
			(-3.56)				
BDI				0.079***	0.266**		
				(3.38)	(2.60)		
BDI * DEPTH					-0.071***		
					(-2.53)		
COMPET1						-2.584***	-5.779***
						(-5.50)	(-3.75)
COMPET1 * DEPTH							1.599***
							(5.05)
SIZE	0.216**	0.208**	0.206**	0.187**	0.192**	0.181**	0.156*
	(2.39)	(2.39)	(2.50)	(2.17)	(2.38)	(2.31)	(1.97)
SIZE_SQR	-0.014**	-0.014**	-0.014**	-0.012**	-0.013**	-0.012**	-0.011**
	(-2.40)	(-2.43)	(-2.55)	(-2.10)	(-2.42)	(-2.35)	(-2.04)
TBTF	-0.562***	-0.540***	-0.605***	-0.535***	-0.444***	-0.373***	-0.358***
	(-3.60)	(-3.54)	(-4.52)	(-3.76)	(-3.54)	(-3.28)	(-3.41)
LOAN	0.058	0.056	0.050	0.060	0.048	0.026	0.035
	(1.11)	(1.04)	(0.96)	(1.18)	(0.93)	(0.52)	(0.71)
EFFICIENCY	-1.132***	-1.133***	-1.143***	-1.149***	-1.158***	-1.202***	-1.187***
	(-5.62)	(-5.61)	(-5.83)	(-5.94)	(-6.12)	(-7.21)	(-6.79)
GDPG	-0.270	0.143	0.034	-0.190	-0.254	1.291	1.306
	(-0.19)	(0.09)	(0.02)	(-0.13)	(-0.19)	(1.14)	(1.30)
INF	-1.884	-1.825	-1.926	-1.587	-1.277	-2.422**	-2.573**
	(-1.51)	(-1.42)	(-1.64)	(-1.42)	(-1.35)	(-2.32)	(-2.53)
CR	0.147	0.119	0.039	0.113	0.130*	0.061	-0.007
	(1.37)	(1.29)	(0.49)	(1.24)	(1.71)	(0.83)	(-0.11)
DEPOSIT_INS	0.042	0.015	0.196	0.020	0.113	-0.018	0.037
	(0.28)	(0.10)	(1.39)	(0.13)	(0.86)	(-0.13)	(0.33)
CAPITAL_STR	0.089**	0.093**	0.106**	0.103**	0.121**	0.093**	0.085**
	(2.05)	(2.02)	(2.28)	(2.42)	(2.61)	(2.22)	(2.17)
ASSET_DIV	0.299**	0.285**	0.239**	0.252**	0.179*	0.163*	0.177*
	(2.36)	(2.22)	(2.24)	(2.09)	(1.83)	(1.68)	(1.98)
Constant	1.438	1.521	2.554***	1.869**	-0.122	-0.047	6.225***
	(1.45)	(1.64)	(3.62)	(2.20)	(-0.11)	(-0.05)	(5.79)
R-squared	0.245	0.245	0.256	0.255	0.263	0.264	0.272
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	86,877	86,877	86,877	86,877	86,877	86,877	86,877

The table presents the regression results for the impact of credit information sharing on bank risk. The dependent variable is bank risk measured by *Z_SCORE_5WIN*. For all these regressions, ROA from five-period rolling window (t, t-1, t-2, t-3 and t-4) are used to calculate the standard deviation of ROA in the Z-Score formula. *Z_SCORE_5WIN* is an indicator of bank stability: *DEPTH* is depth of credit information sharing index; *IFRS* and *BDI* are proxies of information environment; *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *BDI* is a business extent of disclosure index; *COMPET1* is a measure of banking competition converted from Lerner Index; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *SIZE_SQR* is bank size squared; *TBTF* is too-big-too-fail dummy whose value is equal to one if the bank's share in the country's total deposits exceeds 10% and zero otherwise; *LOAN* is a ratio of total gross loans to total assets; *EFFICIENCY* is a ratio of total cost to total income; *GDPG* is real GDP growth; *INF* is inflation; *CR* is creditor rights index; *DEPOSIT_INS* is a dummy for deposit insurance taking a value of one if the country has adopted a deposit insurance regime, and zero otherwise; *CAPITAL_STR* is capital stringency index measuring the extent of both initial and overall capital stringency; *ASSET_DIV* is asset diversification index measuring the extent of bank asset diversification. Further detail of all variables are presented in Table 3-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 3-13: Estimation Results with Alternative Measure of Bank Risk - NPL

Variable	NPL						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DEPTH	-0.010**	-0.007**	-0.008*	-0.010***	-0.005**	-0.010**	0.024
	(-2.61)	(-2.03)	(-1.96)	(-2.65)	(-2.01)	(-2.60)	(1.46)
IFRS		-0.023***	-0.013				
		(-2.75)	(-0.50)				
IFRS * DEPTH			0.002*				
			(1.89)				
BDI				0.001	0.005		
				(0.52)	(0.80)		
BDI * DEPTH					0.001*		
					(1.72)		
COMPET1						0.062	0.176*
						(1.58)	(1.69)
COMPET1 * DEPTH							-0.047**
							(-2.09)
SIZE	-0.001	-0.002	-0.002	-0.001	-0.001	-0.001	-0.000
	(-0.44)	(-0.70)	(-0.66)	(-0.39)	(-0.33)	(-0.35)	(-0.16)
SIZE_SQR	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.44)	(0.36)	(0.31)	(0.35)	(0.22)	(0.37)	(0.18)
TBTF	0.016*	0.018**	0.018**	0.016*	0.017**	0.012	0.013
	(1.85)	(2.41)	(2.38)	(1.85)	(2.01)	(1.41)	(1.53)
LOAN	-0.001	-0.002	-0.002	-0.001	-0.001	0.000	0.000
	(-0.29)	(-0.78)	(-0.88)	(-0.29)	(-0.46)	(0.16)	(0.10)
EFFICIENCY	0.029***	0.029***	0.029***	0.029***	0.029***	0.030***	0.030***
	(6.31)	(6.77)	(6.75)	(6.32)	(6.27)	(7.84)	(7.80)
GDPG	-0.324**	-0.233*	-0.235*	-0.328**	-0.329**	-0.373***	-0.390***
	(-2.18)	(-1.87)	(-1.91)	(-2.18)	(-2.21)	(-2.66)	(-2.89)
INF	0.041	0.040	0.039	0.040	0.043	0.059	0.060
	(0.66)	(0.64)	(0.62)	(0.64)	(0.68)	(1.05)	(1.09)
CR	0.010**	0.006	0.006	0.010**	0.011**	0.011**	0.012***
	(2.20)	(1.50)	(1.36)	(2.25)	(2.25)	(2.42)	(2.71)
DEPOSIT_INS	-0.003	-0.006	-0.005	-0.003	-0.001	-0.003	-0.005
	(-0.22)	(-0.44)	(-0.38)	(-0.21)	(-0.08)	(-0.23)	(-0.39)
CAPITAL_STR	-0.006	-0.006	-0.006	-0.006	-0.006	-0.006	-0.005
	(-1.60)	(-1.57)	(-1.55)	(-1.61)	(-1.57)	(-1.57)	(-1.55)
ASSET_DIV	-0.003	-0.004	-0.004	-0.002	-0.003	0.001	0.001
	(-0.40)	(-0.51)	(-0.53)	(-0.33)	(-0.41)	(0.13)	(0.08)
Constant	0.055	0.063*	0.068**	0.052	0.025	0.103**	-0.071
	(1.53)	(1.83)	(2.01)	(1.46)	(0.46)	(2.35)	(-0.91)
R-squared	0.222	0.231	0.231	0.222	0.223	0.226	0.229
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	75,137	75,137	75,137	75,137	75,137	75,137	75,137

The table presents the regression results for the impact of credit information sharing on bank risk. The dependent variable is bank risk measured by *NPL*. *NPL* is a ratio of total non-performing loans to total gross loans. *DEPTH* is depth of credit information sharing index; *IFRS* and *BDI* are proxies of information environment; *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *BDI* is a business extent of disclosure index; *COMPET1* is a measure of banking competition converted from Lerner Index; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *SIZE_SQR* is bank size squared; *TBTF* is too-big-too-fail dummy whose value is equal to one if the bank's share in the country's total deposits exceeds 10% and zero otherwise; *LOAN* is a ratio of total gross loans to total assets; *EFFICIENCY* is a ratio of total cost to total income; *GDPG* is real GDP growth; *INF* is inflation; *CR* is creditor rights index; *DEPOSIT_INS* is a dummy for deposit insurance taking a value of one if the country has adopted a deposit insurance regime, and zero otherwise; *CAPITAL_STR* is capital stringency index measuring the extent of both initial and overall capital stringency; *ASSET_DIV* is asset diversification index measuring the extent of bank asset diversification.

Further detail of all variables are presented in Table 3-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.
* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 3-14: Estimation Results with Alternative Proxy of Credit Information Sharing - Private Credit Bureau Coverages

Variable	*Z_SCORE*						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
PRIV	0.309**	0.313**	0.268**	0.335**	2.007***	0.338*	0.199**
	(2.32)	(2.40)	(2.36)	(2.52)	(3.06)	(1.75)	(2.58)
IFRS		0.022**	0.664*				
		(2.14)	(1.90)				
IFRS * PRIV			-0.256*				
			(-1.84)				
BDI				0.088*	0.006		
				(1.80)	(0.15)		
BDI * PRIV					-0.257**		
					(-2.41)		
COMPET1						-2.513***	-0.040
						(4.40)	(-0.06)
COMPET1 * PRIV							1.550***
							(3.00)
SIZE	0.190**	0.189**	0.192**	0.163**	0.165**	0.163**	0.148**
	(2.34)	(2.36)	(2.57)	(2.13)	(2.29)	(2.27)	(2.08)
SIZE_SQR	-0.013**	-0.013**	-0.013***	-0.010**	-0.011**	-0.011**	-0.011**
	(-2.43)	(-2.44)	(-2.67)	(-2.14)	(-2.36)	(-2.30)	(-2.21)
TBTF	-0.646***	-0.643***	-0.624***	-0.618***	-0.503***	-0.454***	-0.455***
	(-4.32)	(-4.40)	(-5.03)	(-4.71)	(-4.13)	(-3.94)	(-4.36)
LOAN	0.031	0.031	0.003	0.036	0.031	0.007	0.013
	(0.66)	(0.62)	(0.05)	(0.75)	(0.65)	(0.16)	(0.28)
EFFICIENCY	-1.196***	-1.196***	-1.199***	-1.214***	-1.225***	-1.267***	-1.252***
	(-5.22)	(-5.22)	(-5.29)	(-5.50)	(-5.66)	(-6.43)	(-6.07)
GDPG	1.023	1.097	0.598	1.161	-0.011	2.436**	2.189**
	(0.72)	(0.69)	(0.34)	(0.80)	(-0.01)	(2.18)	(2.28)
INF	-2.590**	-2.590**	-3.019***	-2.291**	-1.877**	-2.983***	-2.738***
	(-2.33)	(-2.32)	(-3.26)	(-2.42)	(-2.12)	(-2.99)	(-3.11)
CR	0.155	0.150	0.005	0.117	0.101	0.069	0.009
	(1.37)	(1.44)	(0.06)	(1.24)	(1.56)	(0.90)	(0.13)
DEPOSIT_INS	0.148	0.144	0.290**	0.112	0.136	0.062	0.216**
	(1.12)	(1.02)	(2.35)	(0.79)	(1.16)	(0.52)	(2.16)
CAPITAL_STR	0.082**	0.082**	0.098**	0.091**	0.105***	0.076**	0.081**
	(2.12)	(2.13)	(2.40)	(2.29)	(2.67)	(2.08)	(2.61)
ASSET_DIV	0.367***	0.366***	0.288**	0.317**	0.272***	0.238**	0.190**
	(2.65)	(2.64)	(2.56)	(2.51)	(2.99)	(2.23)	(2.20)
Constant	2.368***	2.393***	3.137***	2.875***	2.466***	0.818	2.917***
	(2.80)	(2.97)	(5.08)	(4.05)	(3.98)	(0.92)	(4.24)
R-squared	0.234	0.234	0.245	0.243	0.252	0.248	0.254
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	96,422	96,422	96,422	96,422	96,422	96,422	96,422

The table presents the regression results for the impact of credit information sharing on bank risk. Credit information sharing is proxied by private credit bureau coverages *PRIV*. The dependent variable is bank risk measured by *Z_SCORE*. *Z_SCORE* is an indicator of bank stability. *PRIV* is a private credit bureau coverage; *DEPTH* is depth of credit information sharing index; *IFRS* and *BDI* are proxies of information environment; *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *BDI* is a business extent of disclosure index; *COMPET1* is a measure of banking competition converted from Lerner Index; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *SIZE_SQR* is bank size squared; *TBTF* is too-big-too-fail dummy whose value is equal to one if the bank's share in the country's total deposits exceeds 10% and zero otherwise; *LOAN* is a ratio of total gross loans to total assets; *EFFICIENCY* is a ratio of total cost to total income; *GDPG* is real GDP growth; INF is inflation; *CR* is creditor rights index; *DEPOSIT_INS* is a dummy for deposit insurance taking a value of one if the country has adopted a deposit insurance regime, and zero otherwise; *CAPITAL_STR* is capital stringency index measuring the extent of both initial and overall capital stringency; *ASSET_DIV* is asset diversification index measuring the extent of bank asset diversification. Further detail of all variables are presented in Table 3-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.
* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 3-15: Estimation Results with Alternative Proxy of Credit Information Sharing - Public Credit Registry Coverages

Variable	*Z_SCORE*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PUB	0.961	1.052	0.659	0.684	-0.793	0.832	0.435*
	(0.87)	(0.81)	(1.45)	(0.90)	(-0.61)	(0.37)	(1.66)
IFRS		0.102*	0.168*				
		(1.74)	(1.96)				
IFRS * PUB			-0.667				
			(-1.06)				
BDI				0.076***	0.098		
				(3.00)	(0.73)		
BDI * PUB					0.302		
					(1.49)		
COMPET1						-2.380***	-2.692***
						(-3.95)	(-4.12)
COMPET1 * PUB							1.860
							(0.79)
SIZE	0.188**	0.181**	0.180**	0.167**	0.162**	0.164**	0.164**
	(2.27)	(2.28)	(2.28)	(2.11)	(2.06)	(2.28)	(2.28)
SIZE_SQR	-0.012**	-0.012**	-0.012**	-0.011**	-0.011**	-0.011**	-0.011**
	(-2.27)	(-2.30)	(-2.29)	(-2.08)	(-2.08)	(-2.27)	(-2.28)
TBTF	-0.657***	-0.647***	-0.649***	-0.633***	-0.619***	-0.476***	-0.482***
	(-4.53)	(-4.67)	(-4.73)	(-4.98)	(-5.15)	(-4.28)	(-4.43)
LOAN	0.032	0.030	0.031	0.034	0.035	0.008	0.002
	(0.66)	(0.61)	(0.62)	(0.70)	(0.73)	(0.17)	(0.05)
EFFICIENCY	-1.209***	-1.210***	-1.206***	-1.220***	-1.217***	-1.274***	-1.277***
	(-5.50)	(-5.49)	(-5.44)	(-5.65)	(-5.59)	(-6.59)	(-6.67)
GDPG	0.435	0.736	0.462	0.638	0.322	1.798*	1.719
	(0.35)	(0.52)	(0.36)	(0.47)	(0.25)	(1.71)	(1.64)
INF	-2.842***	-2.854***	-2.893***	-2.653***	-2.604***	-3.269***	-3.333***
	(-3.48)	(-3.49)	(-3.45)	(-3.57)	(-3.64)	(-4.20)	(-4.11)
CR	0.157	0.133	0.115	0.134	0.150	0.081	0.064
	(1.34)	(1.30)	(1.19)	(1.33)	(1.55)	(0.97)	(0.78)
DEPOSIT_INS	0.211	0.197	0.191	0.177	0.163	0.130	0.121
	(1.48)	(1.39)	(1.36)	(1.28)	(1.19)	(1.06)	(1.00)
CAPITAL_STR	0.102**	0.106**	0.110**	0.119***	0.124***	0.103**	0.104**
	(2.34)	(2.33)	(2.39)	(2.76)	(2.78)	(2.39)	(2.43)
ASSET_DIV	0.339***	0.329***	0.327***	0.280***	0.241**	0.206**	0.205**
	(2.92)	(2.92)	(2.95)	(2.65)	(2.36)	(2.27)	(2.28)
Constant	2.334**	2.454***	2.510***	2.736***	2.956***	0.841	0.653
	(2.55)	(2.93)	(3.10)	(3.43)	(3.79)	(0.86)	(0.67)
R-squared	0.236	0.236	0.236	0.242	0.244	0.248	0.250
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	96,422	96,422	96,422	96,422	96,422	96,422	96,422

The table presents the regression results for the impact of credit information sharing on bank risk. Credit information sharing is proxied by public credit registry coverage *PUB*. The dependent variable is bank risk measured by *Z_SCORE*. *Z_SCORE* is an indicator of bank stability. *PUB* is a public credit registry coverage; *DEPTH* is depth of credit information sharing index; *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *BDI* is a business extent of disclosure index; *COMPET1* is a measure of banking competition converted from Lerner Index; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *SIZE_SQR* is bank size squared; *TBTF* is too-big-too-fail dummy whose value is equal to one if the bank's share in the country's total deposits exceeds 10% and zero otherwise; *LOAN* is a ratio of total gross loans to total assets; *EFFICIENCY* is a ratio of total cost to total income; *GDPG* is real GDP growth; INF is inflation; *CR* is creditor rights index; *DEPOSIT_INS* is a dummy for deposit insurance taking a value of one if the country has adopted a deposit insurance regime, and zero otherwise; *CAPITAL_STR* is capital stringency index measuring the extent of both initial and overall capital stringency; *ASSET_DIV* is asset diversification index measuring the extent of bank asset diversification. Further detail of all variables are presented in Table 3-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in

all estimations.
*   indicates significance at the 10% level
**   indicates significance at the 5% level
*** indicates significance at the 1% level

Table 3-16: Estimation Results with Alternative Measures of Banking Competition - Banking Concentration Ratios

Variable	*Z_SCORE*				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
DEPTH	0.117**	0.106**	0.126*	0.106**	0.055
	(2.42)	(2.42)	(1.75)	(2.45)	(0.96)
COMPET2		-0.220	0.147		
		(-0.45)	(0.18)		
COMPET2 * DEPTH			-0.071		
			(-0.38)		
COMPET2				-0.245	-1.177
				(-0.66)	(-1.30)
COMPET2 * DEPTH					0.186
					(1.07)
SIZE	0.196**	0.201**	0.200**	0.203**	0.204**
	(2.37)	(2.33)	(2.34)	(2.32)	(2.34)
SIZE_SQR	-0.013**	-0.013**	-0.013**	-0.013**	-0.013**
	(-2.48)	(-2.46)	(-2.46)	(-2.45)	(-2.46)
TBTF	-0.579***	-0.594***	-0.594***	-0.607***	-0.630***
	(-3.62)	(-3.79)	(-3.79)	(-3.81)	(-4.01)
LOAN	0.029	0.032	0.033	0.034	0.034
	(0.59)	(0.72)	(0.74)	(0.74)	(0.76)
EFFICIENCY	-1.204***	-1.200***	-1.200***	-1.199***	-1.200***
	(-5.35)	(-5.30)	(-5.30)	(-5.28)	(-5.31)
GDPG	0.831	0.897	0.892	0.906	1.005
	(0.64)	(0.69)	(0.69)	(0.70)	(0.77)
INF	-2.246**	-2.242**	-2.220**	-2.240**	-2.276**
	(-2.19)	(-2.13)	(-2.09)	(-2.14)	(-2.18)
CR	0.161	0.166	0.168	0.170	0.163
	(1.35)	(1.34)	(1.33)	(1.36)	(1.31)
DEPOSIT_INS	0.115	0.126	0.125	0.137	0.147
	(0.88)	(0.95)	(0.95)	(1.02)	(1.08)
CAPITAL_STR	0.094**	0.090**	0.088**	0.089**	0.095**
	(2.24)	(2.32)	(2.30)	(2.29)	(2.39)
ASSET_DIV	0.338***	0.347***	0.348***	0.345***	0.341***
	(2.69)	(2.68)	(2.67)	(2.68)	(2.67)
Constant	1.828*	1.894*	1.783	1.863*	2.132**
	(1.77)	(1.96)	(1.60)	(1.86)	(2.15)
R-squared	0.235	0.235	0.235	0.235	0.235
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes
Observations	96,422	96,422	96,422	96,422	96,422

The table presents the regression results for the impact of credit information sharing on bank risk. Alternative measures of banking competition are employed, which are *COMPET2* and *COMPET3*. The dependent variable is bank risk measured by *Z_SCORE*. *Z_SCORE* is an indicator of bank stability. *DEPTH* is depth of credit information sharing index; *IFRS* and *BDI* are proxies of information environment; *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *BDI* is a business extent of disclosure index; *COMPET2* is a measure of banking competition converted from concentration index calculated from the fraction of assets held by the 3 largest banks in each country; *COMPET3* is a measure of banking competition converted from concentration index calculated from the fraction of assets held by the 5 largest banks in each country; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *SIZE_SQR* is bank size squared; *TBTF* is too-big-too-fail dummy whose value is equal to one if the bank's share in the country's total deposits exceeds 10% and zero otherwise; *LOAN* is a ratio of total gross loans to total assets; *EFFICIENCY* is a ratio of total cost to total income; *GDPG* is real GDP growth; *INF* is inflation; *CR* is creditor rights index; *DEPOSIT_INS* is a dummy for deposit insurance taking a value of one if the country has adopted a deposit insurance regime, and zero otherwise; *CAPITAL_STR* is capital stringency index measuring the extent of both initial and overall capital stringency; *ASSET_DIV* is asset diversification index measuring the extent of bank asset diversification. Further detail of all variables are presented in Table 3-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 3-17: Estimation Results with Additional Control Variables for the Impact of Credit Information Sharing on Bank Risk

Variable	*Z_SCORE*						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
DEPTH	0.081*	0.086*	0.108**	0.074*	0.085*	0.103**	0.107**
	(1.71)	(1.70)	(2.28)	(1.68)	(1.77)	(2.15)	(2.56)
SIZE	0.175**	0.184**	0.187**	0.180**	0.181**	0.186**	0.200**
	(2.22)	(2.25)	(2.28)	(2.24)	(2.23)	(2.34)	(2.40)
SIZE_SQR	-0.012**	-0.012**	-0.013**	-0.012**	-0.012**	-0.013**	-0.014**
	(-2.39)	(-2.40)	(-2.40)	(-2.41)	(-2.37)	(-2.47)	(-2.60)
TBTF	-0.570***	-0.562***	-0.576***	-0.556***	-0.574***	-0.578***	-0.392***
	(-3.59)	(-3.51)	(-3.63)	(-3.48)	(-3.58)	(-3.62)	(-2.70)
LOAN	0.050	0.043	0.033	0.046	0.046	0.038	0.012
	(0.95)	(0.81)	(0.65)	(0.88)	(0.87)	(0.73)	(0.23)
EFFICIENCY	-1.196***	-1.197***	-1.204***	-1.197***	-1.197***	-1.199***	-1.222***
	(-5.17)	(-5.20)	(-5.32)	(-5.20)	(-5.19)	(-5.22)	(-5.57)
GDPG	1.284	1.139	1.095	1.722	1.261	1.390	-2.130*
	(0.97)	(0.92)	(0.78)	(1.32)	(0.99)	(0.94)	(-1.68)
INF	-1.129	-1.382*	-1.859**	-0.903	-1.317*	-1.704*	-3.127***
	(-1.43)	(-1.79)	(-2.05)	(-1.35)	(-1.76)	(-1.86)	(-2.66)
CR	0.162	0.169	0.158	0.154	0.166	0.162	0.109
	(1.44)	(1.44)	(1.34)	(1.35)	(1.43)	(1.38)	(1.22)
DEPOSIT_INS	0.077	0.075	0.092	0.057	0.084	0.049	0.090
	(0.59)	(0.58)	(0.73)	(0.42)	(0.64)	(0.34)	(0.69)
CAPITAL_STR	0.067	0.070	0.094**	0.056	0.069	0.078	0.134***
	(1.44)	(1.45)	(2.19)	(1.15)	(1.41)	(1.60)	(2.84)
ASSET_DIV	0.312***	0.326***	0.338***	0.346***	0.337***	0.328***	0.302***
	(2.87)	(2.82)	(2.77)	(3.19)	(2.89)	(2.81)	(2.80)
CORRUPTION	0.174**						
	(2.01)						
GOV_EFF		0.155*					
		(1.66)					
POLITIC			0.083				
			(0.82)				
REG_QUA				0.254**			
				(2.04)			
RULE_LAW					0.146		
					(1.65)		
VOICE_ACCT						0.126	
						(1.15)	
PUBLIC_OWN							-1.150***
							(-2.85)
Constant	2.240**	2.100**	1.979*	2.193**	2.155**	2.085**	1.863**
	(2.41)	(2.08)	(1.93)	(2.26)	(2.20)	(2.08)	(2.32)
R-squared	0.239	0.237	0.235	0.238	0.237	0.236	0.250
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	96,422	96,422	96,422	96,422	96,422	96,422	93,059

The table presents the regression results for the impact of credit information sharing on bank risk with additional control variables. The additional control variables are *CORRUPTION, GOV_EFF, POLITIC, REG_QUA, RULE_LAW, VOICE_ACC and PUBLIC_OWN*. The dependent variable is bank risk measured by *Z_SCORE*. *Z_SCORE* is an indicator of bank stability. *DEPTH* is depth of credit information sharing index; *COMPET1* is the 1st competition measure converted from Lerner Index; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *SIZE_SQR* is bank size squared; *TBTF* is too-big-too-fail dummy whose value is equal to one if the bank's share in the country's total deposits exceeds 10% and zero otherwise; *LOAN* is a ratio of total gross loans to total assets; *EFFICIENCY* is a ratio of total cost to total income; *GDPG* is real GDP growth; *INF* is inflation; *CR* is creditor rights index; *DEPOSIT_INS* is a dummy for deposit insurance taking a value of one if the country has adopted a deposit insurance regime, and zero otherwise; *CAPITAL_STR* is capital stringency index measuring the extent of both initial and overall capital stringency; *ASSET_DIV* is asset diversification index measuring the extent of bank asset diversification. *CORRUPTION* is a control of corruption index; *GOV_EFF* is a government effectiveness index; *POLITIC* is a political stability index; *REG_QUA* is a regulatory quality index; *RULE_LAW* is a rule of law index; *VOICE_ACC* is a voice and accountatbility index; *PUBLIC_OWN* is a percentage of total assets in the banking system owned by the government. Further detail of all variables are presented in Table 3-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

* indicates significance at the 10% level

** indicates significance at the 5% level

*** indicates significance at the 1% level

Table 3-18: Estimation Results with Additional Control Variables for the Interaction Effect of Credit Information Sharing and IFRS Adoption on Bank Risk

Variable	*Z_SCORE*						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
DEPTH	0.462**	0.472**	0.490***	0.437**	0.451**	0.486**	0.415***
	(2.25)	(2.29)	(2.94)	(2.12)	(2.24)	(2.53)	(3.38)
IFRS	0.611***	0.633***	0.575***	0.638***	0.623***	0.631***	0.552**
	(3.39)	(-3.24)	(3.10)	(3.33)	(3.26)	(3.13)	(2.46)
IFRS * DEPTH	-0.325***	-0.339***	-0.322***	-0.328***	-0.332***	-0.325***	-0.218***
	(-3.19)	(-3.10)	(-3.01)	(-3.13)	(-3.12)	(-3.04)	(-2.74)
SIZE	0.174**	0.178**	0.184**	0.179**	0.177**	0.185**	0.202**
	(2.39)	(2.39)	(2.44)	(2.41)	(2.37)	(2.50)	(2.45)
SIZE_SQR	-0.012**	-0.012**	-0.013**	-0.012**	-0.012**	-0.013**	-0.014***
	(-2.54)	(-2.56)	(-2.54)	(-2.55)	(-2.52)	(-2.61)	(-2.69)
TBTF	-0.596***	-0.579***	-0.599***	-0.584***	-0.597***	-0.608***	-0.403***
	(-4.30)	(-4.17)	(-4.22)	(-4.18)	(-4.25)	(-4.24)	(-2.83)
LOAN	0.046	0.040	0.028	0.042	0.043	0.035	0.012
	(0.85)	(0.75)	(0.53)	(0.79)	(0.78)	(0.63)	(0.23)
EFFICIENCY	-1.205***	-1.206***	-1.213***	-1.205***	-1.206***	-1.207***	-1.221***
	(-5.29)	(-5.31)	(-5.45)	(-5.32)	(-5.31)	(-5.34)	(-5.54)
GDPG	0.918	0.953	0.804	1.348	0.999	1.005	-1.721
	(0.62)	(0.67)	(0.54)	(0.91)	(0.70)	(0.65)	(-1.36)
INF	-1.198*	-1.302*	-1.925**	-0.938	-1.307*	-1.753**	-2.941**
	(-1.71)	(-1.88)	(-2.28)	(-1.61)	(-1.95)	(-2.11)	(-2.62)
CR	0.076	0.071	0.068	0.069	0.074	0.080	0.055
	(0.88)	(0.82)	(0.80)	(0.80)	(0.85)	(0.93)	(0.69)
DEPOSIT_INS	0.201*	0.187	0.209*	0.182	0.202*	0.172	0.170
	(1.70)	(1.60)	(1.79)	(1.51)	(1.68)	(1.37)	(1.35)
CAPITAL_STR	0.071	0.072	0.100**	0.058	0.072	0.080	0.138***
	(1.44)	(1.38)	(2.15)	(1.13)	(1.36)	(1.51)	(2.83)
ASSET_DIV	0.272***	0.279***	0.297***	0.307***	0.294***	0.290***	0.285***
	(3.01)	(3.01)	(2.87)	(3.48)	(3.11)	(2.94)	(2.72)
CORRUPTION	0.178**						
	(2.25)						
GOV_EFF		0.183*					
		(1.88)					
POLITIC			0.087				
			(0.82)				
REG_QUA				0.266**			
				(2.17)			
RULE_LAW					0.161*		
					(1.78)		
VOICE_ACCT						0.139	
						(1.18)	
PUBLIC_OWN							-0.901**
							(-2.33)
Constant	3.173***	3.141***	2.914***	3.135***	3.148***	3.020***	2.461***
	(4.47)	(4.20)	(3.85)	(4.32)	(4.19)	(3.97)	(3.54)
R-squared	0.246	0.244	0.242	0.245	0.244	0.243	0.253
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	96,422	96,422	96,422	96,422	96,422	96,422	93,059

The table presents the regression results for the impact of information asymmetry (proxied by *IFRS*) on the relationship between credit information sharing and bank risk with additional control variables. The additional control variables are *CORRUPTION, GOV_EFF, POLITIC, REG_QUA, RULE_LAW, VOICE_ACC* and *PUBLIC_OWN.* The dependent variable is bank risk measured by *Z_SCORE. Z_SCORE* is an indicator of bank stability. *DEPTH* is depth of credit information sharing index; *IFRS is a dummy variable indicating whether a country adopts IFRS or not; SIZE* is bank size calculated by taking a natural logarithm of total asset; *SIZE_SQR* is bank size squared; *TBTF* is too-big-too-fail dummy whose value is equal to one if the bank's share in the country's total deposits exceeds 10% and zero otherwise; *LOAN* is a ratio of total gross loans to total assets; *EFFICIENCY* is a ratio of total cost to total income; *GDPG* is real GDP growth; *INF* is inflation; *CR* is creditor rights index; *DEPOSIT_INS* is a dummy for deposit insurance taking a value of one if the country has adopted a deposit insurance regime, and zero otherwise; *CAPITAL_STR* is capital stringency index measuring the extent of both initial and overall capital stringency; *ASSET_DIV* is asset diversification index measuring the extent of bank asset diversification. *CORRUPTION* is a control of corruption index; *GOV_EFF* is a government effectiveness index; *POLITIC* is a political stability index; *REG_QUA* is a regulatory quality index; *RULE_LAW* is a rule of law index; *VOICE_ACC* is a voice and accountability index; *PUBLIC_OWN* is a percentage of total assets in the banking system owned

by the government. Further detail of all variables are presented in Table 3-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.
* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 3-19: Estimation Results with Additional Control Variables for the Interaction Effect of Credit Information Sharing and the Business Extent of Disclosure Index on Bank Risk

Variable	Z_SCORE						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DEPTH	0.479***	0.490***	0.535***	0.474***	0.490***	0.514***	0.376***
	(3.30)	(3.31)	(3.45)	(3.23)	(3.35)	(3.43)	(3.29)
BDI	0.244**	0.250**	0.254**	0.247**	0.251**	0.249**	0.144*
	(2.53)	(2.57)	(2.49)	(2.56)	(2.59)	(2.51)	(1.66)
BDI * DEPTH	-0.067***	-0.069***	-0.071***	-0.068***	-0.069***	-0.069***	-0.045**
	(-3.06)	(-3.11)	(-3.09)	(-3.09)	(-3.14)	(-3.08)	(-2.48)
SIZE	0.162**	0.165**	0.179**	0.161**	0.163**	0.172**	0.186**
	(2.21)	(2.21)	(2.40)	(2.20)	(2.19)	(2.34)	(2.25)
SIZE_SQR	-0.011**	-0.012**	-0.012**	-0.011**	-0.011**	-0.012**	-0.013**
	(-2.40)	(-2.39)	(-2.52)	(-2.39)	(-2.36)	(-2.48)	(-2.48)
TBTF	-0.457***	-0.446***	-0.456***	-0.442***	-0.455***	-0.458***	-0.314**
	(-3.62)	(-3.53)	(-3.66)	(-3.51)	(-3.60)	(-3.64)	(-2.50)
LOAN	0.035	0.032	0.017	0.035	0.034	0.022	0.015
	(0.68)	(0.63)	(0.35)	(0.69)	(0.66)	(0.44)	(0.30)
EFFICIENCY	-1.221***	-1.222***	-1.229***	-1.221***	-1.222***	-1.226***	-1.234***
	(-5.55)	(-5.57)	(-5.73)	(-5.56)	(-5.56)	(-5.66)	(-5.75)
GDPG	0.938	0.885	0.450	1.386	0.972	0.729	-1.739
	(0.72)	(0.71)	(0.34)	(1.03)	(0.76)	(0.53)	(-1.56)
INF	-0.965	-0.979	-1.907***	-0.553	-0.949	-1.573**	-2.277***
	(-1.49)	(-1.62)	(-2.65)	(-1.04)	(-1.60)	(-2.17)	(-2.65)
CR	0.140*	0.145*	0.138*	0.133*	0.143*	0.138*	0.100
	(1.73)	(1.75)	(1.67)	(1.68)	(1.75)	(1.67)	(1.38)
DEPOSIT_INS	0.139	0.133	0.181	0.115	0.141	0.154	0.150
	(1.10)	(1.08)	(1.43)	(0.90)	(1.11)	(1.22)	(1.24)
CAPITAL_STR	0.102**	0.102**	0.123***	0.088*	0.101**	0.119**	0.149***
	(2.21)	(2.10)	(2.77)	(1.85)	(2.06)	(2.45)	(3.07)
ASSET_DIV	0.210**	0.213**	0.215**	0.230***	0.222**	0.219**	0.240***
	(2.43)	(2.43)	(2.38)	(2.89)	(2.57)	(2.44)	(2.66)
CORRUPTION	0.113*						
	(1.79)						
GOV_EFF		0.122*					
		(1.67)					
POLITIC			-0.060				
			(-0.88)				
REG_QUA				0.211**			
				(2.19)			
RULE_LAW					0.113		
					(1.58)		
VOICE_ACCT						0.020	
						(0.27)	
PUBLIC_OWN							-0.801**
							(-2.43)
Constant	0.635	0.547	0.197	0.657	0.579	0.375	0.898
	(0.57)	(0.47)	(0.16)	(0.58)	(0.50)	(0.31)	(0.93)
R-squared	0.251	0.251	0.250	0.252	0.251	0.250	0.259
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	96,422	96,422	96,422	96,422	96,422	96,422	93,059

The table presents the regression results for the impact of information asymmetry (proxied by *BDI*) on the relationship between credit information sharing and bank risk with additional control variables. The additional control variables are *CORRUPTION, GOV_EFF, POLITIC, REG_QUA, RULE_LAW, VOICE_ACC* and *PUBLIC_OWN*. The dependent variable is bank risk measured by *Z_SCORE*. *Z_SCORE* is an indicator of bank stability. *DEPTH* is depth of credit information sharing index; *BDI is a business extent of disclosure index; SIZE* is bank size calculated by taking a natural logarithm of total asset; *SIZE_SQR* is bank size squared; *TBTF* is too-big-too-fail dummy whose value is equal to one if the bank's share in the country's total deposits exceeds 10% and zero

otherwise; *LOAN* is a ratio of total gross loans to total assets; *EFFICIENCY* is a ratio of total cost to total income; *GDPG* is real GDP growth; *INF* is inflation; *CR* is creditor rights index; *DEPOSIT_INS* is a dummy for deposit insurance taking a value of one if the country has adopted a deposit insurance regime, and zero otherwise; *CAPITAL STR* is capital stringency index measuring the extent of both initial and overall capital stringency; *ASSET_DIV* is asset diversification index measuring the extent of bank asset diversification. *CORRUPTION* is a control of corruption index; *GOV_EFF* is a government effectiveness index; *POLITIC* is a political stability index; *REG_QUA* is a regulatory quality index; *RULE_LAW* is a rule of law index; *VOICE_ACC* is a voice and accountability index; *PUBLIC_OWN* is a percentage of total assets in the banking system owned by the government. Further detail of all variables are presented in Table 3-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.
*   indicates significance at the 10% level
**   indicates significance at the 5% level
*** indicates significance at the 1% level

Table 3-20: Estimation Results with Additional Control Variables for the Interaction Effect of Credit Information Sharing and Banking Competition on Bank Risk

Variable	Z_SCORE						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DEPTH	-0.799***	-0.861***	-0.888***	-0.834***	-0.832***	-0.868***	-0.838***
	(-3.24)	(-3.32)	(-3.51)	(-3.23)	(-3.28)	(-3.34)	(-3.04)
COMPET1	-3.602**	-4.044**	-4.413***	-3.802**	-3.847**	-4.204**	-4.366***
	(-2.30)	(-2.52)	(-2.80)	(-2.39)	(-2.43)	(-2.58)	(-2.68)
COMPET1 * DEPTH	1.178***	1.265***	1.332***	1.217***	1.227***	1.297***	1.264***
	(3.33)	(3.42)	(3.69)	(3.31)	(3.38)	(3.51)	(3.32)
SIZE	0.132*	0.138*	0.138*	0.136*	0.136*	0.138*	0.186**
	(1.84)	(1.91)	(1.92)	(1.90)	(1.88)	(1.95)	(2.24)
SIZE_SQR	-0.010**	-0.010**	-0.010**	-0.010**	-0.010**	-0.010**	-0.013**
	(-2.05)	(-2.09)	(-2.05)	(-2.09)	(-2.05)	(-2.12)	(-2.35)
TBTF	-0.385***	-0.375***	-0.391***	-0.372***	-0.389***	-0.391***	-0.322***
	(-3.31)	(-3.23)	(-3.53)	(-3.19)	(-3.35)	(-3.42)	(-2.84)
LOAN	0.034	0.030	0.021	0.031	0.031	0.025	0.017
	(0.65)	(0.57)	(0.41)	(0.59)	(0.60)	(0.50)	(0.33)
EFFICIENCY	-1.258***	-1.258***	-1.263***	-1.258***	-1.258***	-1.258***	-1.259***
	(-6.17)	(-6.19)	(-6.32)	(-6.20)	(-6.19)	(-6.20)	(-6.13)
GDPG	2.883***	2.799***	2.820***	3.334***	2.893***	3.144***	1.258
	(2.94)	(3.00)	(2.83)	(3.68)	(3.12)	(3.07)	(1.06)
INF	-1.708***	-1.861***	-2.263***	-1.456***	-1.849***	-2.134***	-2.762***
	(-2.81)	(-2.92)	(-3.07)	(-2.64)	(-3.01)	(-2.87)	(-2.97)
CR	0.037	0.041	0.026	0.027	0.039	0.032	0.029
	(0.53)	(0.58)	(0.38)	(0.39)	(0.56)	(0.46)	(0.42)
DEPOSIT_INS	0.056	0.054	0.069	0.037	0.063	0.019	0.090
	(0.54)	(0.52)	(0.66)	(0.36)	(0.61)	(0.17)	(0.73)
CAPITAL_STR	0.069	0.070	0.095**	0.058	0.071	0.076	0.126***
	(1.53)	(1.48)	(2.28)	(1.20)	(1.45)	(1.59)	(2.80)
ASSET_DIV	0.178**	0.190**	0.204**	0.210***	0.201**	0.191**	0.183*
	(2.28)	(2.32)	(2.40)	(2.63)	(2.37)	(2.28)	(1.85)
CORRUPTION	0.166**						
	(2.31)						
GOV_EFF		0.164*					
		(1.75)					
POLITIC			0.108				
			(1.21)				
REG_QUA				0.249**			
				(2.33)			
RULE_LAW					0.146*		
					(1.78)		
VOICE_ACCT						0.149	
						(1.61)	
PUBLIC_OWN							-0.467
							(-1.26)
Constant	5.296***	5.521***	5.702***	5.410***	5.412***	5.657***	5.258***
	(4.75)	(4.95)	(5.18)	(4.82)	(4.89)	(4.94)	(4.72)
R-squared	0.256	0.255	0.254	0.256	0.255	0.254	0.258
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	96,422	96,422	96,422	96,422	96,422	96,422	93,059

The table presents the regression results for the impact of banking competition on the relationship between credit information sharing and bank risk with additional control variables. The additional control variables are *CORRUPTION, GOV_EFF, POLITIC, REG_QUA, RULE_LAW, VOICE_ACC* and *PUBLIC_OWN.* The dependent variable is bank risk measured by *Z_SCORE*. *Z_SCORE* is an indicator of bank stability. *DEPTH* is depth of credit information sharing index; *COMPET1* is the 1st competition measure converted from Lerner Index; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *SIZE_SQR* is bank size squared; *TBTF* is too-big-too-fail dummy whose value is equal to one if the bank's share in the country's total deposits exceeds 10% and zero otherwise; *LOAN* is a ratio of total gross loans to total assets; *EFFICIENCY* is a ratio of total cost to total income; *GDPG* is real GDP growth; INF is inflation; *CR* is creditor rights index; *DEPOSIT_INS* is a dummy for deposit insurance taking a value of one if the country has adopted a deposit insurance regime, and zero otherwise; *CAPITAL_STR* is capital stringency index measuring the extent of both initial and overall capital stringency; *ASSET_DIV* is asset diversification index measuring the extent of bank asset diversification. *CORRUPTION* is a control of corruption index; *GOV_EFF* is a government effectiveness index; *POLITIC* is a political stability index; *REG_QUA* is a regulatory quality index; *RULE_LAW* is a rule of law index; *VOICE_ACC* is a voice and accountability index; *PUBLIC_OWN* is a percentage of total assets in the banking system owned by the government. Further detail of all variables are presented in Table 3-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 3-21: Sub Sample Analysis by Information Asymmetry

Variable	*Z_SCORE*		*Z_SCORE*	
	NON-IFRS Adoption	**IFRS Adoption**	**LOW BDI**	**HIGH BDI**
	(1)	**(2)**	**(3)**	**(4)**
DEPTH	0.139**	0.013*	0.140***	0.001
	(2.46)	(1.69)	(3.48)	(0.02)
SIZE	0.321	0.127	0.218	0.116
	(1.66)	(1.28)	(1.65)	(1.24)
SIZE_SQR	-0.019*	-0.009	-0.015**	-0.008
	(-1.69)	(-1.25)	(-2.13)	(-1.23)
TBTF	-0.595***	-0.485***	-0.029	-0.556***
	(-3.69)	(-2.75)	(-0.15)	(-3.86)
LOAN	0.032	0.029	0.073	0.008
	(0.80)	(0.41)	(1.36)	(0.12)
EFFICIENCY	-0.904***	-1.415***	-0.878***	-1.396***
	(-13.04)	(-8.00)	(-11.70)	(-7.29)
GDPG	4.884**	-0.938	0.480	0.992
	(2.11)	(-0.80)	(0.33)	(0.90)
INF	-2.324**	-2.384**	-2.363**	-2.261***
	(-2.62)	(-2.05)	(-2.30)	(-3.39)
CR	0.097	-0.115	0.154	-0.061**
	(1.11)	(-1.29)	(1.33)	(-2.56)
DEPOSIT_INS	-0.118	0.194	0.043	0.181
	(-0.32)	(1.09)	(0.22)	(1.30)
CAPITAL_STR	0.114	0.023	0.186***	0.038
	(1.49)	(0.58)	(3.51)	(1.49)
ASSET_DIV	0.188*	0.158	0.210*	-0.064
	(1.77)	(1.15)	(1.88)	(-1.02)
Constant	-1.363	3.372***	0.302	3.765***
	(-0.92)	(7.12)	(0.36)	(9.26)
R-squared	0.276	0.227	0.303	0.226
Bank Fixed Effects	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
Observations	27,990	68,432	28,949	67,473

The table presents the regression results of subsample analysis for the impact of credit information sharing on bank risk. The subsamples are classified based on proxies of information environment. "NON-IFRS" is the group of observations with NON-IFRS adoption proxied for low transparent information environment, while "IFRS" is the group of observations with IFRS adoption proxied for high transparent information environment. "LOW BDI" is the group of observations with BDI below the median value of the sample, while "HIGH BDI" is the group of observations with BDI above the median value of the sample. The dependent variable is bank risk measured by *Z_SCORE*. *Z_SCORE* is an indicator of bank stability. *DEPTH* is depth of credit information sharing index; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *SIZE_SQR* is bank size squared; *TBTF* is too-big-too-fail dummy whose value is equal to one if the bank's share in the country's total deposits exceeds 10% and zero otherwise; *LOAN* is a ratio of total gross loans to total assets; *EFFICIENCY* is a ratio of total cost to total income; *GDPG* is real GDP growth; *INF* is inflation; *CR* is creditor rights index; *DEPOSIT_INS* is a dummy for deposit insurance taking a value of one if the country has adopted a deposit insurance regime, and zero otherwise; *CAPITAL_STR* is capital stringency index measuring the extent of both initial and overall capital stringency; *ASSET_DIV* is asset diversification index measuring the extent of bank asset diversification. Further detail of all variables are presented in Table 3-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 3-22: Sub Sample Analysis by Banking Competition

Variable	*Z_SCORE*		*Z_SCORE*		*Z_SCORE*	
	COMPET1 (TOP 25)	**COMPET1 (BOTTOM 25)**	**COMPET1 (TOP 30)**	**COMPET1 (BOTTOM 30)**	**COMPET1 (TOP 40)**	**COMPET1 (BOTTOM 40)**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
DEPTH	0.267***	0.052	0.262***	0.048	0.172***	0.051
	(3.39)	(1.64)	(3.38)	(1.64)	(3.01)	(1.58)
SIZE	0.165	0.087	0.177	0.093	0.167	0.104
	(1.01)	(0.93)	(1.28)	(1.23)	(1.60)	(1.30)
SIZE_SQR	-0.013	-0.006	-0.013*	-0.006	-0.013**	-0.008
	(-1.45)	(-0.93)	(-1.78)	(-1.24)	(-2.13)	(-1.34)
TBTF	-0.466*	-0.430**	-0.466**	-0.461***	-0.400**	-0.409**
	(-1.86)	(-2.30)	(-2.15)	(-2.89)	(-2.24)	(-2.43)
LOAN	0.019	-0.060	0.040	-0.045	0.038	-0.042
	(0.54)	(-1.32)	(0.88)	(-0.99)	(0.81)	(-0.90)
EFFICIENCY	-0.728***	-1.711***	-0.858***	-1.673***	-0.978***	-1.620***
	(-6.47)	(-9.19)	(-7.08)	(-8.07)	(-6.15)	(-10.14)
GDPG	3.039	-1.840	3.511	-2.713*	3.727**	-1.332
	(1.16)	(-1.27)	(1.40)	(-1.86)	(2.05)	(-1.06)
INF	-1.861	-1.320*	-2.080	-1.519**	-2.658**	-1.552**
	(-1.36)	(-1.91)	(-1.45)	(-2.25)	(-2.21)	(-2.35)
CR	0.108	0.010	0.063	-0.011	0.150*	-0.023
	(1.17)	(0.27)	(0.66)	(-0.30)	(1.68)	(-0.62)
DEPOSIT_INS	0.355	0.037	0.388*	0.094	0.333*	0.118
	(1.37)	(0.23)	(1.67)	(0.67)	(1.76)	(0.84)
CAPITAL_STR	0.299**	0.057**	0.189**	0.007	0.175**	0.003
	(2.34)	(2.06)	(2.37)	(0.21)	(2.42)	(0.09)
ASSET_DIV	0.241*	-0.007	0.279**	-0.093	0.374***	-0.078
	(1.74)	(-0.09)	(2.05)	(-1.32)	(3.92)	(-1.08)
Constant	-0.513	3.651***	-0.356	4.124***	0.419	4.074***
	(-0.75)	(12.16)	(-0.53)	(16.91)	(0.58)	(15.58)
R-squared	0.300	0.232	0.277	0.228	0.282	0.240
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,608	28,599	29,913	30,172	39,783	36,814

The table presents the regression results of subsample analysis for the impact of credit information sharing on bank risk. The subsamples are classified based on the banking competition measure *COMPET1*. "TOP" and "BOTTOM" on each column are observations "above" and "below" the percentile of *COMPET1,* respectively.

The dependent variable is bank risk measured by *Z_SCORE*. *Z_SCORE* is an indicator of bank stability. *DEPTH* is depth of credit information sharing index; *COMPET1* is the 1st competition measure converted from Lerner Index; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *SIZE_SQR* is bank size squared; *TBTF* is too-big-too-fail dummy whose value is equal to one if the bank's share in the country's total deposits exceeds 10% and zero otherwise; *LOAN* is a ratio of total gross loans to total assets; *EFFICIENCY* is a ratio of total cost to total income; *GDPG* is real GDP growth; *INF* is inflation; *CR* is creditor rights index; *DEPOSIT_INS* is a dummy for deposit insurance taking a value of one if the country has adopted a deposit insurance regime, and zero otherwise; *CAPITAL_STR* is capital stringency index measuring the extent of both initial and overall capital stringency; *ASSET_DIV* is asset diversification index measuring the extent of bank asset diversification. Further detail of all variables are presented in Table 3-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the country-level are applied in all estimations.

* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 3-23: Non-US Sample Analysis

Variable	Z_SCORE						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DEPTH	0.124**	0.123**	0.480**	0.111**	0.517***	0.092**	0.091***
	(2.38)	(2.25)	(2.39)	(2.36)	(3.48)	(2.49)	(4.19)
IFRS		0.022*	0.518***				
		(1.88)	(3.16)				
IFRS * DEPTH			-0.311***				
			(-2.95)				
BDI				0.091***	0.279***		
				(3.39)	(2.63)		
BDI * DEPTH					-0.061***		
					(-3.19)		
COMPET1						-2.058***	-5.686***
						(-3.46)	(-3.81)
COMPET1 * DEPTH							1.525***
							(4.38)
SIZE	0.152*	0.153*	0.146**	0.120	0.118*	0.126*	0.098
	(1.92)	(1.95)	(1.98)	(1.65)	(1.82)	(1.88)	(1.58)
SIZE_SQR	-0.010**	-0.010**	-0.010**	-0.008*	-0.008**	-0.009**	-0.007*
	(-2.16)	(-2.17)	(-2.22)	(-1.79)	(-2.06)	(-2.05)	(-1.78)
TBTF	-0.558***	-0.560***	-0.604***	-0.540***	-0.462***	-0.437***	-0.416***
	(-3.70)	(-3.71)	(-4.37)	(-4.07)	(-3.93)	(-3.64)	(-3.71)
LOAN	0.051	0.051	0.058	0.063	0.065	0.042	0.053
	(1.29)	(1.33)	(1.65)	(1.57)	(1.65)	(1.04)	(1.39)
EFFICIENCY	-0.771***	-0.771***	-0.779***	-0.800***	-0.802***	-0.875***	-0.862***
	(-13.69)	(-13.68)	(-13.30)	(-12.01)	(-11.97)	(-13.78)	(-14.16)
GDPG	2.176	2.106	1.665	2.407*	1.918	2.378*	2.145*
	(1.42)	(1.18)	(1.08)	(1.68)	(1.65)	(1.81)	(1.78)
INF	-2.676***	-2.690***	-2.716***	-2.356***	-1.966***	-3.020***	-3.002***
	(-2.83)	(-2.70)	(-2.82)	(-2.97)	(-2.97)	(-3.40)	(-3.55)
CR	0.117	0.119	0.066	0.103	0.163*	0.086	0.016
	(1.03)	(1.15)	(0.73)	(1.10)	(1.92)	(0.90)	(0.19)
DEPOSIT_INS	0.112	0.117	0.240**	0.097	0.211*	0.042	0.067
	(1.02)	(1.01)	(2.03)	(0.81)	(1.82)	(0.38)	(0.66)
CAPITAL_STR	0.099**	0.099**	0.080*	0.092**	0.078*	0.088*	0.095**
	(2.16)	(2.16)	(1.87)	(2.06)	(1.85)	(1.98)	(2.15)
ASSET_DIV	0.196*	0.194*	0.226**	0.178*	0.193**	0.166*	0.169**
	(1.70)	(1.71)	(2.11)	(1.85)	(2.39)	(1.81)	(1.99)
Constant	1.439	1.423	2.323***	1.900**	-0.278	0.338	6.218***
	(1.44)	(1.47)	(3.47)	(2.30)	(-0.23)	(0.32)	(5.46)
R-squared	0.239	0.239	0.250	0.257	0.269	0.254	0.266
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	45,773	45,773	45,773	45,773	45,773	45,773	45,773

The table presents the regression results of subsample analysis for the impact of credit information sharing on bank risk. All regressions exclude banks in the USA. The dependent variable is bank risk measured by *Z_SCORE*. *Z_SCORE* is an indicator of bank stability. *DEPTH* is depth of credit information sharing index; *IFRS* and *BDI* are proxies of information environment; *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *BDI* is a business extent of disclosure index; *COMPET1* is a measure of banking competition converted from Lerner Index; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *SIZE_SQR* is bank size squared; *TBTF* is too-big-too-fail dummy whose value is equal to one if the bank's share in the country's total deposits exceeds 10% and zero otherwise; *LOAN* is a ratio of total gross loans to total assets; *EFFICIENCY* is a ratio of total cost to total income; *GDPG* is real GDP growth; *INF* is inflation; *CR* is creditor rights index; *DEPOSIT_INS* is a dummy for deposit insurance taking a value of one if the country has adopted a deposit insurance regime, and zero otherwise; *CAPITAL_STR* is capital stringency index measuring the extent of both initial and overall capital stringency; *ASSET_DIV* is asset diversification index measuring the extent of bank asset diversification. Further detail of all variables are presented in Table 3-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 3-24: IV Approach for the Impact of Credit Information Sharing on Bank Risk

Variable	*Z_SCORE*	
	(1)	(2)
DEPTH	0.312*	
	(1.78)	
SIZE	0.246***	-0.014
	(2.71)	(-0.25)
SIZE_SQR	-0.016***	0.001
	(-2.67)	(0.20)
TBTF	-0.400*	-0.576***
	(-1.70)	(-2.74)
LOAN	0.006	0.025
	(0.10)	(1.14)
EFFICIENCY	-1.269***	0.020
	(-6.16)	(0.77)
GDPG	0.488	3.849
	(0.26)	(1.64)
INF	-1.486	-4.971***
	(-0.71)	(-3.14)
CR	0.078	0.132
	(0.75)	(1.05)
DEPOSIT_INS	-0.075	0.928*
	(-0.26)	(1.93)
CAPITAL_STR	0.048	0.129
	(0.74)	(1.46)
ASSET_DIV	0.423**	-0.223
	(2.36)	(-1.44)
LEGALORIGIN		1.954***
		(4.55)
ETHNIC_FRAC		-1.330***
		(-2.86)
LATITUDE		-1.480*
		(-1.80)
Constant	0.394	4.717***
	(0.25)	(4.66)
R-squared	0.233	0.514
First Stage F-test	8.402	
Second Stage F-test	80.98	
Hansen J	3.24	
Hansen J P-Value	0.196	
Observations	87,300	87,300

The table presents the results of instrumental variable regressions for the impact of credit information sharing on bank risk. The instruments are legal origins, ethnic fractionalization, and latitude. The 2nd-stage regressions are reported in the odd columns, while the 1st-stage regressions are reported in the even columns.
The dependent variable is bank risk measured by *Z_SCORE*. *Z_SCORE* is an indicator of bank stability. *DEPTH* is depth of credit information sharing index; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *SIZE_SQR* is bank size squared; *TBTF* is too-big-too-fail dummy whose value is equal to one if the bank's share in the country's total deposits exceeds 10% and zero otherwise; *LOAN* is a ratio of total gross loans to total assets; *EFFICIENCY* is a ratio of total cost to total income; *GDPG* is real GDP growth; *INF* is inflation; *CR* is creditor rights index; *DEPOSIT_INS* is a dummy for deposit insurance taking a value of one if the country has adopted a deposit insurance regime, and zero otherwise; *CAPITAL_STR* is capital stringency index measuring the extent of both initial and overall capital stringency; *ASSET_DIV* is asset diversification index measuring the extent of bank asset diversification; *LEGALORIGIN* is dummy variable whose value is equal to one if a country has English legal origin and otherwise zero; *ETHNIC_FRAC* is an ethnic fractionalization which captures the ethnic diversity in a country; *LATITUDE* is a latitude which measures the geographical latitude of a country. Further detail of all variables are presented in Table 3-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.
* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 3-25: IV Approach for the Effect of Information Asymmetry on the Linkage between Credit Information Sharing and Bank Risk

Variable	*Z_SCORE*							
	IFRS Adoption		**NON IFRS Adoption**		**HIGH BDI**		**LOW BDI**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
DEPTH	0.201*		0.781**		-0.074		0.122*	
	(1.86)		(2.28)		(-1.63)		(1.74)	
SIZE	0.395**	-0.056	0.234**	0.136**	0.149	0.049	0.368**	0.064
	(2.75)	(-0.79)	(2.24)	(2.56)	(1.54)	(0.70)	(1.99)	(0.81)
SIZE_SQR	-0.024*	0.005	-0.016**	-0.008**	-0.011	-0.003	-0.024**	-0.003
	(-1.89)	(1.27)	(-1.99)	(-2.52)	(-1.55)	(-0.79)	(-2.29)	(-0.63)
TBTF	-0.456*	-0.104	-0.661***	-0.655***	-0.538***	0.110	0.000	-1.170***
	(-1.71)	(-0.41)	(-2.71)	(-3.32)	(-3.42)	(0.87)	(0.00)	(-5.49)
LOAN	-0.021	0.017	0.036	0.047	0.005	0.003	0.052	0.037
	(-0.52)	(0.67)	(0.29)	(1.64)	(0.07)	(0.24)	(0.47)	(1.26)
EFFICIENCY	-0.872***	0.058	-1.436***	0.006	-1.398***	0.017	-0.874***	0.134**
	(-10.88)	(1.35)	(-8.41)	(0.39)	(-7.30)	(0.93)	(-10.32)	(2.27)
GDPG	9.064**	-1.121	-5.325**	1.628	1.625	0.606	-2.501	1.140
	(2.23)	(-0.25)	(-2.04)	(0.60)	(1.15)	(0.22)	(-0.76)	(0.42)
INF	2.007	-9.250***	-2.241**	-1.333	-2.158**	-3.909*	-3.380	-4.526*
	(0.44)	(-4.80)	(-1.96)	(-1.01)	(-2.56)	(-1.78)	(-1.59)	(-1.93)
CR	-0.211	0.394***	-0.001	0.261*	-0.053**	0.175*	0.214	0.161
	(-0.80)	(3.84)	(-0.01)	(1.83)	(-2.30)	(1.73)	(1.63)	(1.13)
DEPOSIT_INS	0.201	-0.420	0.874***	1.227***	0.421**	2.114***	0.029	0.214
	(0.46)	(-0.74)	(2.92)	(3.67)	(2.08)	(3.83)	(0.11)	(0.62)
CAPITAL_STR	0.206	-0.012	0.089	0.336***	0.065*	-0.017	0.282***	0.130
	(1.44)	(-0.15)	(1.36)	(3.33)	(1.84)	(-0.21)	(3.07)	(1.43)
ASSET_DIV	0.178	0.231	0.188*	-0.290	-0.049	-0.249	-0.104	-0.128
	(0.91)	(1.45)	(1.75)	(-1.43)	(-0.76)	(-1.12)	(-0.51)	(-0.51)
LEGALORIGIN		0.855		0.050		2.415***		-0.472
		(1.13)		(0.07)		(6.39)		(-0.65)
ETHNIC_FRAC		-2.414***		-2.080***		-0.745		-2.453***
		(-3.69)		(-4.77)		(-1.55)		(-5.94)
LATITUDE		-1.487		-0.380		-3.903***		1.006
		(-1.44)		(-0.29)		(-3.07)		(0.99)
Constant	-2.113	6.105***	4.646***	2.553***	4.130***	4.797***	1.264	3.973***
	(-1.05)	(6.22)	(9.10)	(2.76)	(11.07)	(5.62)	(1.33)	(4.47)
R-squared	0.288	0.589	0.230	0.653	0.226	0.713	0.281	0.640
First Stage F-test	5.552		7.798		31.49		11.89	
Second Stage F-test	29.54		658.1		267.3		274.4	
Hansen J	1.863		0.02		0.40		4.233	
Hansen J P-Value	0.30		0.98		0.523		0.121	
Observations	25,850	25,850	61,450	61,450	65,680	65,680	21,620	21,620

The table presents the results of instrumental variable regressions for the impact of credit information sharing on bank risk. The instruments are legal origins, ethnic fractionalization, and latitude. The subsamples are classified based on proxies of information environment. "NON-IFRS" is the group of observations with NON-IFRS adoption proxied for low transparent information environment, while "IFRS" is the group of observations with IFRS adoption proxied for high transparent information environment. "LOW BDI" is the group of observations with BDI below the median value of the sample, while "HIGH BDI" is the group of observations with BDI above the median value of the sample. The 2nd-stage regressions are reported in the odd columns, while the 1st-stage regressions are reported in the even columns.

The dependent variable is bank risk measured by *Z_SCORE*. *Z_SCORE* is an indicator of bank stability. *DEPTH* is depth of credit information sharing index; *IFRS* and *BDI* are proxies of information environment; *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *BDI* is a business extent of disclosure index; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *SIZE_SQR* is bank size squared; *TBTF* is too-big-too-fail dummy whose value is equal to one if the bank's share in the country's total deposits exceeds 10% and zero otherwise; *LOAN* is a ratio of total gross loans to total assets; *EFFICIENCY* is a ratio of total cost to total income; *GDPG* is real GDP growth; *INF* is inflation; *CR* is creditor rights index; *DEPOSIT_INS* is a dummy for deposit insurance taking a value of one if the country has adopted a deposit insurance regime, and zero otherwise; *CAPITAL_STR* is capital stringency index measuring the extent of both initial and overall capital stringency; *ASSET DIV* is asset diversification index measuring the extent of bank asset diversification; *LEGALORIGIN* is dummy variable whose value is equal to one if a country has English legal origin and otherwise zero; *ETHNIC_FRAC* is an ethnic fractionalization which captures the ethnic diversity in a country; *LATITUDE* is a latitude which measures the geographical latitude of a country. Further detail of all variables are presented in Table 3-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all

estimations.
*   indicates significance at the 10% level
**   indicates significance at the 5% level
*** indicates significance at the 1% level

Table 3-26: IV Approach for the Effect of Banking Competition on the Linkage between Credit Information Sharing and Bank Risk

Variable	*Z_SCORE*			
	HIGH COMPET1		**LOW COMPET1**	
	(1)	**(2)**	**(3)**	**(4)**
DEPTH	0.316**		0.033	
	(2.35)		(0.57)	
SIZE	0.247	-0.006	0.120	0.016
	(1.62)	(-0.06)	(1.42)	(0.33)
SIZE_SQR	-0.017*	-0.001	-0.009	0.001
	(-1.88)	(-0.17)	(-1.49)	(0.36)
TBTF	-0.250	-0.853***	-0.368*	-0.550**
	(-0.99)	(-3.55)	(-1.90)	(-2.20)
LOAN	0.017	-0.007	-0.043	0.073**
	(0.21)	(-0.26)	(-0.85)	(2.48)
EFFICIENCY	-1.027***	0.006	-1.633***	0.037
	(-6.38)	(0.24)	(-10.77)	(1.16)
GDPG	3.471	-0.983	-2.546	12.565***
	(0.96)	(-0.28)	(-1.55)	(2.98)
INF	-2.635	-3.380	-1.568**	-4.284**
	(-1.31)	(-1.12)	(-1.98)	(-2.55)
CR	0.038	0.343***	-0.030	-0.085
	(0.25)	(3.66)	(-0.81)	(-0.64)
DEPOSIT_INS	0.188	0.405	0.296	1.381**
	(0.68)	(1.11)	(1.58)	(2.27)
CAPITAL_STR	0.116	0.069	0.017	0.177
	(1.10)	(0.80)	(0.46)	(1.51)
ASSET_DIV	0.295**	-0.206	-0.035	-0.247
	(2.41)	(-1.18)	(-0.41)	(-1.06)
LEGALORIGIN		1.976***		1.857***
		(3.11)		(3.15)
ETHNIC_FRAC		-0.588		-3.229***
		(-1.56)		(-3.87)
LATITUDE		-0.570		-2.523*
		(-0.56)		(-1.95)
Constant	-0.524	4.565***	4.491***	4.904***
	(-0.47)	(4.09)	(11.10)	(3.31)
R-squared	0.281	0.606	0.242	0.602
First Stage F-test	3.637		6.224	
Second Stage F-test	150		201.7	
Hansen J	1.68		1.51	
Hansen J P-Value	0.512		0.45	
Observations	33,039	33,039	35,552	35,552

The table presents the results of instrumental variable regressions for the impact of credit information sharing on bank risk. The instruments are legal origins, ethnic fractionalization, and latitude. The subsamples are classified based on the measure of banking competition *COMPET1*. "TOP" and "BOTTOM" are observations "above" and "below" the 30 percentile of *COMPET1* in each year respectively. The 2nd-stage regressions are reported in the odd columns, while the 1st-stage regressions are reported in the even columns.

The dependent variable is bank risk measured by *Z_SCORE*. *Z_SCORE* is an indicator of bank stability. *DEPTH* is depth of credit information sharing index; *COMPET1* is the 1st competition measure converted from Lerner Index; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *SIZE_SQR* is bank size squared; *TBTF* is too-big-too-fail dummy whose value is equal to one if the bank's share in the country's total deposits exceeds 10% and zero otherwise; *LOAN* is a ratio of total gross loans to total assets; *EFFICIENCY* is a ratio of total cost to total income; *GDPG* is real GDP growth; *INF* is inflation; *CR* is creditor rights index; *DEPOSIT_INS* is a dummy for deposit insurance taking a value of one if the country has adopted a deposit insurance regime, and zero otherwise; *CAPITAL_STR* is capital stringency index measuring the extent of both initial and overall capital stringency; *ASSET_DIV* is asset diversification index measuring the extent of bank asset diversification; *LEGALORIGIN* is dummy variable whose value is equal to one if a country has English legal origin and otherwise zero; *ETHNIC_FRAC* is an ethnic fractionalization which captures the ethnic diversity in a country; *LATITUDE* is a latitude which measures the geographical latitude of a country. Further detail of all variables are presented in Table 3-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 3-27: Additional Test for the Impact of Credit Information Sharing on Bank Risk – The Role of Creditor Rights

Variable	*Z_SCORE*	
	LOW CR	**HIGH CR**
	(1)	**(2)**
DEPTH	0.097	0.134***
	(1.36)	(3.50)
COMPET1	1.340	2.220***
	(1.40)	(3.97)
SIZE	0.266**	0.109
	(2.11)	(1.18)
SIZE_SQR	-0.020**	-0.007
	(-2.17)	(-1.27)
TBTF	-0.340*	-0.503***
	(-1.85)	(-4.51)
LOAN	0.000	0.004
	(0.00)	(0.10)
EFFICIENCY	-1.410***	-0.935***
	(-7.32)	(-11.55)
GDPG	-1.190	3.478**
	(-0.44)	(2.57)
INF	-5.684**	-1.981***
	(-2.10)	(-2.92)
DEPOSIT_INS	-0.316	0.080
	(-0.83)	(0.52)
CAPITAL_STR	0.067	0.085
	(1.39)	(1.45)
ASSET_DIV	0.315*	0.191
	(1.76)	(1.60)
Constant	2.735***	-0.001
	(4.32)	(-0.00)
R-squared	0.241	0.264
Bank Fixed Effects	Yes	Yes
Time Dummies	Yes	Yes
Observations	60,393	36,896

The table presents the regression results for the impact of credit information sharing on bank risk grouped by the level of creditor rights index. "LOW CR" is the group of observations with CR values below the sample median value, while "HIGH CR" is the group of observations with CR values above the sample median value. The dependent variable is bank risk measured by *Z_SCORE*. *Z_SCORE* is an indicator of bank stability. *DEPTH* is depth of credit information sharing index; *COMPET1* is the 1st competition measure converted from Lerner Index; *SIZE* is bank size calculated by taking a natural logarithm of total asset; *SIZE_SQR* is bank size squared; *TBTF* is too-big-too-fail dummy whose value is equal to one if the bank's share in the country's total deposits exceeds 10% and zero otherwise; *LOAN* is a ratio of total gross loans to total assets; *EFFICIENCY* is a ratio of total cost to total income; *GDPG* is real GDP growth; *INF* is inflation; *CR* is creditor rights index; *DEPOSIT_INS* is a dummy for deposit insurance taking a value of one if the country has adopted a deposit insurance regime, and zero otherwise; *CAPITAL STR* is capital stringency index measuring the extent of both initial and overall capital stringency; *ASSET_DIV* is asset diversification index measuring the extent of bank asset diversification. Further detail of all variables are presented in Table 3-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

* indicates significance at the 10% level

** indicates significance at the 5% level

*** indicates significance at the 1% level

Chapter 4: Credit Information Sharing and Bank Stock Price Crash Risk: The Role of Information Asymmetry and Bank Regulations

4.1 Introduction

In the previous chapter, we examine the impact of credit information sharing on bank risk based on the asymmetric information between banks and borrowers. However, risk, especially downside risk or the risk of extreme losses, may arise from the asymmetric information between banks and outside investors. It is the ability to make loans that generate such asymmetric information between banks and outside investors. When banks make loans, they possess private information about borrowers, and the credit quality of borrowers is not readily observable and accessible by outside investors. This bank opacity enables corruption in lending and gives lending officers incentives to conceal any bad projects or adverse operating outcomes for an extended period. Eventually, the unanticipated release of hoarding negative information may lead to the risk of extreme losses, namely crash risk.

Interest in crash risk has been increasing, particularly since the 2008 financial crisis. In the onset of the crisis, investors' lack of confidence and fear of further decreases in prices have been identified among the various culprits behind the sharp price declines (Kim *et al.* 2013). Crash risk is an essential characteristic of return distribution and captures asymmetry in risk, especially downside risk or extreme negative return. Thus, it is important for portfolio theories, asset-pricing and option-pricing models (Kim *et al.* 2014; Kim & Zhang 2015). Unlike the risks from symmetric volatilities, the risk of extreme losses, or crash risk, cannot be reduced through portfolio diversification (Mitton & Vorkink 2007; Barberis & Huang 2008; Sunder 2010; Kim *et al.* 2011b; Conrad *et al.* 2013).

Several mechanisms have been identified in the literature as the source of crash risk. These mechanisms are referred to leverage effects (Black 1976; Christie 1982), investor heterogeneity (Romer 1993; Hong & Stein 2003) and volatility feedback effects (French *et al.* 1987; Campbell & Hentschel 1992). Another factor that increasingly captures much of attention in the crash risk literature is the information opacity that provides corporate managers incentives to conceal bad news (negative information) from outside investors (Jin & Myers 2006; Hutton *et al.* 2009). This information theory requires neither disagreement among investors nor time variation in risk premia (Hutton *et al.* 2009).

A wide range of incentives, such as compensation contracts, career concerns, and empire building, motivate corporate insiders to hide unfavorable outcome from their poor performance (Ball 2009; Kothari *et al.* 2009). If an insider conceals or hoards bad news (negative information) for an extended period, the firm's share price may be overvalued, creating a bubble. When the bad news accumulates and reaches its upper limit that can no longer be absorbed, that bad news will be suddenly released to the stock market all at once; as a consequence, the bubble bursts and a stock market crash (Jin & Myers 2006; Hutton *et al.* 2009). More importantly, hiding bad news about a firm prevents investors and board of directors to take an early action to correct or liquidate bad projects. As a consequence, unprofitable projects are kept alive and their poor performances are piled up over time until a collapse of asset price occurs (Bleck & Liu 2007).

As suggested by Hertzberg *et al.* (2010), the incentive of bad news hoarding inside banks is due to a loan officer's career concern. This poses a principle-agent problem inside banks that may lead to mistakenly unintentional communication toward outside investors. Specifically, due to career concern, a loan officer (agent) tends to hide information about their assigned borrower's repayment prospect that reflects poorly on their own performance. This hidden negative information eventually prevents investors and the board of directors from taking timely abandonment actions or discerning negative net present value (NPV) projects at an early stage (Bleck & Liu 2007).

Due to potentially bad news hoarding behaviors, we argue that credit information sharing among banks about their borrowers' creditworthiness will discourage bank loan officers to engage in bad news hoarding behaviors and subsequently lead to a reduction in stock price crash risk. We base on our prediction on these following reasons. First, credit information sharing helps to monitor loan officers and to prevent corruption in lending. Second, sharing of borrowers from one bank will be beneficial to another bank's manager validating internal risk ratings and will prevent loan officers from being bias in their reports about borrowers. Third, credit information sharing improves comparability that discourages bad news hoarding within banks. Thus, more credit information sharing can improve bank transparency and help to curb bad news hoarding activities of loan officers. Consequently, the perception of investors about banks' true underlying performance is improved and the risk of stock price crash is suppressed. How, and to what extent, credit information sharing among banks helps reducing crash risk is an empirical question.

The impact of credit information sharing may also depend on the transparency of the information environment. In an environment with a greater level of information transparency, bank loan officers have less ability to conceal negative information about borrowers as more information is assessable to both investors and loan managers. When the information environment is more transparent, the impact of credit information sharing on crash risk should then be less pronounced. Thus, like the previous two chapters, we also examine the impact of information asymmetry on the relationship between credit information sharing and crash risk (see figure 4-1).

Furthermore, a banking industry is known to be heavily regulated by regulators and authorities because they play an essential role in channeling savings to the most productive investment projects and thereby enhance the performance of economies (Barth *et al.* 2004; Levine 2004, 2005). Regulation and supervision are considered as an additional external governance force that acts macro-economically at the banking industry level and micro-economically at the individual bank level (Barth *et al.* 2006; Beck *et al.* 2006b; De Andres & Vallelado 2008). When the banking regulatory environments are strict, banks are less likely to have enormous discretion to act in their own interests rather than in the interests of shareholders and debt holders. Thus, the impact of credit information sharing on crash risk may depend on the strictness of banking regulatory environments (see figure 4-2).

For our empirical investigation, we use a cross-country sample of international bank-level data during 2005 to 2013. Following prior literature on stock price crash risk (Chen *et al.* 2001; Hutton *et al.* 2009; Kim *et al.* 2011b, a; An *et al.* 2015), we measure the crash risk of individual banks by the negative skewness of firm-specific weekly returns and the asymmetric volatility of negative and positive stock returns. Crash risk captures return skewness (the third moment of stock return), which is distinct from measures studied in prior research, such as the average return (the first moment) and the variance of returns (the second moment).

The results indicate that credit information sharing through public credit registries reduces bank-specific stock price crash risk, whereas the depth of credit information sharing and information sharing through private credit bureaus have no significant effect on crash risk. These findings show that banks in a country with more credit information sharing through public credit registries are less likely to experience crash risk. These findings are consistent with our conjecture that borrower information sharing may prevent banks' loan officers from hiding bad news that could lead to a future stock price crash. The insignificance of information sharing through private credit bureaus on crash risk suggests that the voluntary exchange of credit information among banks may not be sufficient to prevent bad news hoarding. Banks may self-select themselves into sharing credit information and may share only information that makes them better off. Moreover, private credit bureaus are not compulsory and less regulated than the public credit registries (Majnoni *et al.* 2004). Therefore, opaque banks may not join the credit bureaus to share borrower information in the first place.

Furthermore, we proxy the level of information transparency environment by the mandatory adoption of IFRS and find that the impact of credit information sharing on crash risk is less pronounced with more transparent information environment. With regards to banking regulatory environments, we analyze three aspects of bank regulations related to the three pillars of the Basel Accords, namely capital adequacy, official supervisory power and market discipline. We find that the impact of credit information sharing on crash risk is more pronounced with less stringent capital requirements, low supervisory power and low degree of private monitoring. These findings suggest that credit information sharing is more useful in reducing crash risk when the banking regulatory environments are weak. Overall, our results are robust to an alternative measure of crash risk, additional controls, subsample analysis and potential endogeneity.

Our research in this chapter contributes to the literature in two ways. First, our study adds to the growing literature on banks' credit information sharing and its economic consequences. As discussed earlier, prior works in this area has studied the impact of credit information sharing on enhanced credit availability (Pagano & Jappelli 1993; Padilla & Pagano 1997; Djankov *et al.* 2007; Brown *et al.* 2009), in lowering cost of credit (Brown *et al.* 2009), in reducing borrower-default rate (Jappelli & Pagano 2002), in reducing bank-lending corruption (Barth *et al.* 2009), in reducing bank risk (Houston *et al.* 2010) & banking crisis (Büyükkarabacak & Valev 2012), in increasing industrial growth (Houston *et al.* 2010) and in enhancing job growth (Ayyagari *et al.* 2016). We add to the literature by investigating the role of credit information sharing in reducing bank-specific stock price crash risk, which captures asymmetry in risk or the third moment of the stock return distribution. This role is distinct from the effect of credit information sharing on stock return performance (first moment) or firm risk (second moment) documented in prior studies. Thus, our findings broaden the understanding of the economic consequences of credit information sharing on banks and investors.

Second, our research contributes to the emerging literature that attempts to forecast future stock price crash risk (Chen *et al.* 2001; Hong & Stein 2003; Jin & Myers 2006; Hutton *et al.* 2009; Kim *et al.* 2011b, a; Kim *et al.* 2014; Kim & Zhang 2015). The literature on crash risk has captured much attention from both the investment community and academic researchers since the stock market collapse of 2001-2002 and 2008-2009. We complement prior studies on crash risk by examining a new factor that mitigates future stock price crash risk. By examining crash risk, our study will be beneficial to firms, shareholders and investors who might want to manage tail risk in the stock market and incorporate crash risk in their portfolio and risk management decisions (Harvey & Siddique 2000; Chen *et al.* 2001).

In summary, this chapter attempts to answer these following questions, which are graphically displayed in Figure 4-1 and Figure 4-2:

1. How, and to what extent, credit information sharing affects bank-specific stock price crash risk?
2. How, and to what extent, information asymmetry (as measured by IFRS adoption and BDI) and bank regulations & supervision affect the relationship between credit information sharing and bank-specific stock price crash risk?

The remainder of the chapter is structured as follows. Section 2 reviews the related literature and outlines hypotheses development. Section 3 describes data and methodology.

Section 4 discusses the empirical results, the robustness tests, and the additional tests. Section 5 presents our conclusions.

4.2 Literature Review and Hypotheses Development

4.2.1 Stock Price Crash Risk

It has been well documented that the distribution of stock returns exhibits negative skewness; that is, large negative stock returns (or stock price crashes) are more common than large positive stock price movements (French *et al.* 1987; Campbell & Hentschel 1992; Bekaert & Wu 2000; Chen *et al.* 2001; Hong & Stein 2003). Following Chen *et al.* (2001) and Hutton *et al.* (2009), we define crash risk as a negative skewness of firm-specific weekly return distribution.

Several mechanisms could initiate crash risk or, more generally, negative skewness in returns. Perhaps the most venerable theory is based on leverage effects (Black 1976; Christie 1982), whereby a drop in prices raises operating and financial leverage, and hence the volatility of subsequent returns. However, it appears that leverage effects are not of sufficient quantitative importance to explain the data (Schwert 1989; Bekaert & Wu 2000). This is especially true if one is interested in asymmetries at a relatively high frequency, e.g., in daily data. To explain these, one has to argue that intraday changes in leverage have a large impact on volatility – that a drop in prices on Monday morning leads to a large increase in leverage and hence in volatility by Monday afternoon so that overall, the return for the full day Monday is negatively skewed. Another explanation for asymmetries in stock market returns comes from stochastic bubble models of the sort pioneered by Blanchard and Watson (1982). The asymmetry here is due to the popping of the bubble – a low-probability event that produces large negative returns.

Investor heterogeneity is another source of existence of negative asymmetries in market returns. For instance, as in the paper by Romer (1993), in the absence of new fundamental information and irrationality, the trading among investors who have different opinions could reveal the private signals of others and move prices. This process, combined with short sale constraints, discloses an asymmetry in which market declines differentially reveal the private signals of relatively pessimistic investors (Hong & Stein 2003). Such revelation could lead other investors to downgrade their assessments of a firm's prospects, thereby reinforcing the decline. Motivated by difference-of-opinion, Chen *et al.* (2001) examine what factors determine the negative skewness in the daily returns of individual stocks and conclude that past returns and recent deviation of turnover are the most significant.

Volatility feedback effects could also be the cause of negative skewness (French *et al.* 1987; Campbell & Hentschel 1992). For example, big price movements could cause investors to reassess market volatility and increase required risk premia. When a large piece of good news arrives, this signals that market volatility has increased, so the direct positive effects of the good news is partially offset by an increase in the risk premium. In contrast, when the bad news arrives, the direct effects and the effect of the risk-premium now go in the same direction. Thus, the impact of the news is amplified with the bad news.

Another factor, which is the focus of this chapter, that appear in the literature as an important predictor of stock price crash risk is the managerial incentives to conceal bad corporate news from outside investors (Jin & Myers 2006; Hutton *et al.* 2009; Kothari *et al.* 2009). This growing body of research focuses on the significant positive relationship between crash risk and the consequence of managerial concealing bad news as long as possible (i.e. bad news hoarding behaviors). In a nutshell, managers have an incentive to conceal and accumulate bad news due to career and compensation concerns; however, when the accumulation of bad news eventually reaches its upper limit, all accumulated bad news suddenly becomes publicly available resulting in a large decline in a stock price, namely a stock price crash (Jin & Myers 2006; Hutton *et al.* 2009).

The linkage between managerial tendency to hoard bad news and stock price crash risk starts with the theoretical analysis by Jin and Myers (2006). This model does not rely on the disagreement among investors or time variation in risk-premia. Instead, the model is based on the firm's extreme information asymmetry. Particularly, firms' managers have control at least a portion of the public access to the firm's fundamental information through disclosure about their firms' operations as well as their firms' asset values (Basu 1997; Kothari *et al.* 2009). Managers, in such firms, due to career concerns and incentives arising from compensation contracts, may exploit information asymmetries by concealing negative information and engaging in short-sighted price maximization to better serve their own interests (Stein 1989; Kothari *et al.* 2009; Andreou *et al.* 2015).

Career concern may motivate managers to work hard and generate good performance (Holmstrom 1982; Holmström 1999); however, career concerns may also motivate managers to conceal bad news and gamble that subsequent events will turn in their favor, enabling them to bury the bad news (Kothari *et al.* 2009). As defined broadly by Kothari *et al.* (2009), managers' career concerns include the impact of disclosure on current monetary incentives such as stock/option-based incentives and bonus plans, as well as the long-horizon effects of disclosures on promotion, employment opportunities, and potential termination. Therefore, if their compensation links to their earnings performance, they tend to hide any information that could negatively affect their earnings and, hence, compensation (Basu 1997; Kothari *et al.* 2009). Consistent with the view that managers tend to conceal bad news, the survey from Graham *et al.* (2005) suggests that managers with bad news tend to delay disclosure more than do those with good news. Kothari *et al.* (2009) also contend that managers will announce good news immediately to investors; however, they will act strategically towards bad news by weighing the cost and benefits before disclosing such bad news.

There are various ways that managers can engage in bad news hoarding behaviors. Kothari *et al.* (2009) argue that managers have an incentive to stockpile bad news by overstating financial statement. Focusing on dividend changes and management earnings forecasts, they provide evidence that managers delay the release of bad news to investors. Furthermore, managers' short-termist behavior may involve the manipulation of nonfinancial information. Managers can pursue suboptimal investment decision that caters to prevailing market sentiment and to support the pretense of strong investment opportunities (Bebchuk & Stole 1993; McNichols & Stubben 2008; Kedia & Philippon 2009; Benmelech *et al.* 2010). For instance, in the period of overstated earnings, managers overinvest in property, plant, and equipment (McNichols & Stubben 2008). In addition, firms may involve in too excessive hiring and investing during periods of inflated performance (Kedia & Philippon 2009). In the theoretical model of Benmelech *et al.* (2010), after the slowdown of the growth rate, suboptimal investment decision leads to undercapitalization and finally results in stock price crash. In addition, Ball (2001) and Ball (2009) argues that nonfinancial motives, such as empire building and maintaining the esteem of one's peers, also motivate managers to hide bad performance. Managers can build up their empire by pretending to have valuable investment opportunities, which is, in turn, masked by presenting the firm's good performance (Xu *et al.* 2014).

Anecdotal evidence during the past 2 decades also highlights the issue of concealing and hoarding bad news. According to Powers *et al.* (2002), Enron set up off-balance-sheet Special Purpose Vehicles to hide assets that were losing money until accumulated losses were no longer sustainable. Arthur Anderson was also accused of destroying documentation related to its audit of Enron (Abdel-Khalik 2016). According to Beresford *et al.* (2003), WorldCom used fraudulent accounting methods to mask a declining earnings trend until the accounting data were no longer deemed realistic. According to Schapiro (2010), New Century failed to disclosure dramatic increases in early default rates, loan repurchases, and pending loan repurchase requests until this was no longer sustainable with the collapse of the subprime mortgage business. Lakonishok *et al.* (1991) show that pension fund managers, by "window dress" their portfolio, tend to oversell losing stocks (stocks that have performed poorly) before annual evaluation. Similarly, Musto (1999) show that retail money market fund managers switch to safer investment around disclosure. The tendency to hide bad news may involve issue outside finance. For instance, police downgrade offense classifications to understate crime incidence (Seidman & Couzens 1974), school teachers cheat on standardized tests to improve student scores (Jacob & Levitt 2003; Levitt & Dubner 2005), etc.

As a consequence, the accumulation of bad news within firms is the culprit behind the occurrence of the stock price crash risk. The managerial tendency to conceal, delay or accumulate the announcement of bad news leads to bad news being withheld within the firm. Eventually, the accumulation of bad news reaches a certain threshold at which it becomes too costly or impossible for managers to continue withholding the bad news and the resulting negative cash flows eventually materialize (Jin & Myers 2006; Hutton *et al.* 2009; Kothari *et al.* 2009). The consequence of the sudden release of all accumulated hidden bad news to the public results in a large negative price decline (share-price collapse), that is, a significant stock price crash (Jin & Myers 2006; Bleck & Liu 2007; Hutton *et al.* 2009; Benmelech *et al.* 2010; Callen & Fang 2013). This crash refers to a large negative outlier in the distribution of returns generating long left tails in the distribution of stock return (Chen *et al.* 2001; Hong & Stein 2003).

Bleck and Liu (2007) argue that the withholding of bad news prevents investors and the board of directors from discriminating bad projects (with negative net present value) from good ones and, therefore, prevent them from liquidating bad projects promptly or forcing managers to take timely actions at the early stage. The hiding of bad news also allows firms with aggressive accounting to keep bad projects for a longer period, compared to firms with conservative accounting (Francis & Martin 2010; Ahmed & Duellman 2011). As a result, unprofitable projects are kept alive and poor performance accumulates over time until an asset price crash (Bleck & Liu 2007; Kim *et al.* 2011b).

There are several prior studies supporting the consequence of managerial tendency to withhold bad news on stock price crash risk. Those studies are quite recent. The first set of evidence shows that stock price crash risk increases with financial accounting opacity, corporate tax avoidance, executive-equity incentive and excess perks. Using international data, Jin and Myers (2006) find that country-level crash risk is positively associated with country-level financial reporting opacity. Corroborating Jin and Myers (2006), Hutton *et al.* (2009) employ US firm-level data and find that crash risk is positively related to financial reporting opacity, as measured by discretional accruals (earnings management measure). In line with Hutton *et al.* (2009), Kim and Zhang (2014) and DeFond *et al.* (2014) further document that the opaqueness of financial reports is associated with future stock price crash risk. Particularly, Kim and Zhang (2014) show that, besides discretional accruals, the occurrence of financial statement restatements and the presence of auditor-attested material internal control weakness increase crash risk. On the other hand, DeFond *et al.* (2014) use a more comprehensive measure of financial reporting transparency than discretionary accruals and find that increased financial transparency after the adoption of IFRS decreases crash risk among non-financial firms.

In addition, Kim *et al.* (2011b) show the positive association between crash risk and tax avoidance. They argue that managers hide news through complex tax shelters to extract private benefits at the expense of shareholders, which then leads to an unexpected stock crash once all the bad news is unveiled. Moreover, Kim *et al.* (2011a) find that the chief financial officer's (CFO) option incentive, as measured by the sensitivity of the option portfolio value to stock price, is positively related to the firm's future stock price crash risk. They argue that stock options-based compensation induces managers to behave short-termist so they have an incentive to board bad news to inflate current share price at the expense of long-term firm-value. In a context of China, Xu *et al.* (2014) find that excess perks provide executives an incentive to hide bad news for extended periods so that they can continue to collect their perks and thus their firms are prone to crash risk.

In contrary, the second set of evidence finds that crash risk decreases with dedicated institutional investors' ownership, corporate social responsibility performance, accounting conservatism, high levels of religiosity and increased financial statement comparability. By testing the two competing view of the roles of institutional investors' ownership monitoring versus short-termism on managerial bad news hoarding activities, An and Zhang (2013) and Callen and Fang (2013) find that US firms' crash risk decreases with dedicated & stable institutional investors' ownership, which has a strong monitoring incentive, a large stakeholding and a long investment horizon. However, crash risk increases with transient institutional investors' ownership due to weaker monitoring, smaller holdings, and short-termism. Consistent with An and Zhang (2013) and Callen and Fang (2013), Chauhan *et al.* (2015) provide similar results for Indian firms. A few studies have explored the role of corporate social responsibility on crash risk but have found contradicting results. Corporate social responsibility has reduced the crash risk for firms in the US (Kim *et al.* 2014) and Taiwan (Lee & Lee 2016). However, it has no effect on reducing crash risk of Japanese firms (Jie & Nakajima 2014).

Moreover, Kim and Zhang (2015) find that the timelier recognition of bad news as losses than of good news as gains (or conditional conservatism) reduces crash risk. In addition to Kim and Zhang (2015), Kousenidis *et al.* (2014) provide evidence that not only conditional conservatism that reduces crash risk but also unconditional conservatism, which is news-independent. By examining the view that short sellers are sophisticated investors who are able to identify bad news hoarding by managers (i.e. firms) whose stock they short in anticipation of price crashes, Callen and Fang (2015b) find robust evidence that short selling is significantly related to crash risk. In another paper by Callen and Fang (2015a), they suggest the view that religion, as a set of social norms, could help limiting managerial bad news hoarding activities. To be specific, they find that firms located in the US countries who headquartered in countries with high levels of religiosity experience low levels of crash risk.

Kim *et al.* (2016) focus on the benefit of financial statement comparability based on the study of De Franco *et al.* (2011) and argue that financial statement comparability reduces managers' incentives and ability to hoard bad news because investors can obtain some of the undisclosed bad news of a firm from analyzing or inferring from its comparable peer firms. Empirically, they find evidence that crash risk decreases with improved comparable financial statements.

In contrast to prior crash risk literature that focus upon a single governance mechanism (Hutton *et al.* 2009; Kim *et al.* 2011a; An & Zhang 2013; Callen & Fang 2013; Kim & Zhang 2015), Andreou *et al.* (2015) undertake a comprehensive investigation using a board set of governance attributes in order to measure the overall quality of a firm's governance mechanisms in association with a firm's propensity to stock price crash. Of all 4 central governance mechanisms, they find that ownership structure and accounting opacity are the first and second most significant factor, respectively, in affecting the crash risk. In contrast, board structure & processes and managerial incentives explain very little a firm's tendency to stock price crash. By further analyzing each individual 21 attributes, they show that crash risk increases with transient institutional ownership (similar to An and Zhang (2013), Callen and Fang (2013) and Chauhan *et al.* (2015)), CEO stock-option incentive (similar to Kim *et al.* (2011a)) and the proportion of outside director that hold equity in the company; whereas, crash risk decreases with insiders' ownership, the level of accounting conservatism in financial reports (similar to Kim and Zhang (2015)), the size of the board and the presence of corporate governance policy in the company's mandate.

4.2.2 Credit Information Sharing and Stock Price Crash Risk

Like nonfinancial firms, a bank's corporate governance is no different. Banks are firms with debt holders, shareholders board of directors, etc. One can view the governance of banks in a similar way as the governance of the automobile companies, pharmaceutical companies, etc. Due to banks' similarity toward nonfinancial firms, when a bank is less transparent, its manager (like any other managers) has an incentive to stockpile bad news due to career concerns. There is a limit to which bad news can be hidden and accumulated within the firm. When the hidden bad news accumulated over time reaches its threshold, it is released all at once, resulting in a stock price crash (Jin & Myers 2006; Hutton *et al.* 2009).

However, banks are generally less transparent than nonfinancial firms (Ross 1989; Levine 2004). Evidence from Furfine (2001) suggests that the problem of information asymmetry is common in all sectors but it is larger in a banking sector. It is the ability of banks to make loans and their trading assets that make them more opaque than nonfinancial firms (Morgan 2002; Flannery *et al.* 2004). The quality of loan is not readily observable and can even be hidden for a long period of time because banks possess information relating to the credit quality of the borrowers (a borrower's creditworthiness) as well as the characteristics of the loan contracts that is not accessible by outside investors (Levine 2004). Moreover, in the banking sector, their assets are inherently opaque and difficult to value by outside investors (Ross 1989; Morgan 2002; Cheng *et al.* 2011; Gorton 2013; Andreou *et al.* 2015). Banks can also modify the risk composition of their assets more quickly compared to nonfinancial firms and they can hide problems by extending loans to clients that cannot service previous debt obligations (Levine 2004).

Thus, the source of bank's opacity can be found in the loan quality and its allocation (Morgan 2002; Levine 2003; Flannery *et al.* 2004). In this sense, banks' transparency may improve with more credit information sharing among banks about their borrowers' creditworthiness. Enhanced transparency then discourages bad news hoardings within banks. However, whether or not sharing information among banks about borrowers enhances banks' transparency and helps to curb bad news hoarding behaviors within banks and subsequently reduces stock price crash risk is an empirical question.

Previous studies link loan officers' bad news hoarding behaviors to their career concern. Hertzberg *et al.* (2010) show that the incentive of bad news hoarding inside banks is due to a loan officer's career concern. This poses a principle-agent problem inside banks that may lead to mistakenly unintentional communication toward outside investors. Due to career concern, a loan officer (agent) tends to hide information that reflects poorly on their own performance. That is a loan officer has an incentive to hide bad news about their assigned borrower's repayment prospect (Hertzberg *et al.* 2010). This hidden incentive is no different from the incentive taken by an employee in nonfinancial firms.

In a lending process, a loan officer performs a dual role, active monitoring, and passive monitoring. The active monitoring states that the role of a loan officer is to manage the relationship with a firm so as to maintain high repayment prospects. Besides, the active monitoring, the passive monitoring states that a loan officer is also responsible for obtaining and reporting information about the firm's repayment prospects. Loan officers make lending recommendations based on their assessment of each firm's creditworthiness and communicate their assessment by internally assigning risk ratings. This role of passive monitoring allows a loan officer to hide bad news and suppress unfavorable information about repayment prospects because it will reflect poorly on how she has performed as an active monitor (Hertzberg *et al.* 2010). For instance, loan officers can assign lower-than-reality default probability for their assigned borrowers when they are actually more likely to default.

Hertzberg *et al.* (2010) suggest that there is a mechanism in which it can prevent loan officers from withholding bad news due to career concerns. They show evidence that a rotation policy can mitigate the agency problem in communication between loan officers and their managers by temporarily separating the active and passive monitoring. A firm will be reassigned to a different loan officer at the end of the rotation period[23] of firm-loan officer relationship. Their results show that a loan officer (agent) has reduced incentives to suppress bad news about his or her assigned borrowers when his or her relationship manager (principle) can compare the officer's report with that issued by the successor. Also, when the time of rotation comes, reports issued by loan officers are more accurate, more informative internal risk ratings (more predictive power of a borrower's creditworthiness) and contains more bad news about borrowers' repayment prospects.

The rotation policy is effective because the new loan officer will have an incentive to report bad news immediately to demonstrate their early-bad-news-detecting ability and to avoid bad news that can reflect poorly upon his or her future performance record (Hertzberg *et al.* 2010). Moreover, loan officers who fail to report bad news and are exposed by their successor may go on to manage the smaller lending portfolio as one of punishment schemes. Thus, the ex-ante threat of being uncovered by a newly loan officer will reduce the incentive of incumbent loan officers to withhold bad news and induce incumbent loan officers to perform self-reporting bad news, which has the smaller negative impact on their career

[23] They base on the 3-year loan officer rotation rule from the Argentina branch of a large multinational U.S bank to identify the effect of rotation on the reporting behavior of loan officers.

prospects.

In addition to the rotation policy, we argue that the role of credit information sharing can play an important role in constraining loan officers' discretion and incentives to hoard bad news. Due to imperfect information in the lending process, the loan officer has a significant amount of discretion in terms of the lending decision, such as loan rates, maturities, or type of collateral required, if any. Such amount of discretion creates a room for bribery and leads to corruption in lending (Barth *et al.* 2009). The loan officers could have an incentive to request for a bribe to improve his or her income. At the same time, borrowers could also have an incentive to bribe the loan officer to seek loans that provide better terms, such as longer maturities, lower loan rates, or loans without collateral. Supporting the role of credit information sharing on monitoring loan officers, Barth *et al.* (2009) argue that credit information sharing can reduce lending corruption by lowering the degree of discretion of loan officers that can be exercised in evaluating loan applicants and improving the monitoring of loan officers. Thus, information sharing may also curb loan officers' tendency to conceal bad news to their superiors.

Moreover, relationship managers can gain access to information shared on a credit bureau/registry to partly validate the internal risk ratings assigned by loan officers and ensure that the information content from reports issued by loan officers is less bias. Thus, higher extensiveness of credit information sharing system improves the validation of internal risk ratings by allowing managers to compare them with external risk ratings assigned to the same borrowers by other banks.

In addition, information sharing among banks about their borrowers may enhance comparability, which helps discourage loan officers from being bias in his or her report. Recent literature shows that financial statement comparability reduces the cost of acquiring and processing information and raises the quality of financial information (De Franco *et al.* 2011; Barth *et al.* 2012; Kim *et al.* 2013)[24]. Supporting the effect of financial statement

[24] For instance, Comparability facilities transfer of information across comparable firms such that their economic similarity and differences can be inferred smartly (De Franco et al. 2011). Another example, the improvement of financial statement comparability helps investors in understanding and evaluating firm performance because less judgmental calculations with accounting numbers and fewer adjustment are required when comparing a firm's performance with that of its peers (Kim et al. 2013).

comparability on firms' bad news hoardings, Kim *et al.* (2016) argue that investors gain a better understanding of a performance of a firm and also obtain some of the bad news by inferring the performance and/or disclosure of the firm's comparable peers. Specifically, they examine whether financial statement comparability predicts crash risk and find that comparability reduces firms' future crash risk.

From the comparability literature, we can form two arguments. First, we argue that credit information sharing can reduce the tendency of loan officers to hide bad news by allowing their superiors to gain more borrowers' information and able to compare with their peers. Second, if we consider banks as investors, credit information sharing can also improve comparability and allow each of them to gain more knowledge about the repayment prospect of other banks' borrowers (or default risk). Therefore, credit information sharing does not only limit loan officers' bad news hoarding behaviors but also all banks' managers.

Taken together, we argue that the extensive availability and better scope of credit information sharing among banks will prevent banks, especially banks' loan officer, from withholding bad news due to the following rationales. First, credit information sharing help monitoring loan officers and preventing corruption in lending. Second, the sharing of borrowers from one bank will be beneficial to another bank's manager validating internal risk ratings and preventing loan officers from being bias in their reports about borrowers. Third, credit information sharing improves comparability that discourages bad news hoarding within banks. Thus, more credit information sharing reduces bad news hoarding activities within banks and therefore improve investors' perception about banks' true underlying performance. In other words, banks in a country with more credit information sharing through either private credit bureau or public credit registry is less likely to experience crash risk.

Based on the arguments that bad news withholding creates stock price crash risk and that the extensiveness of credit information sharing exerts prevention of bad news hoarding behaviors within banks, we hypothesize that more credit information sharing is expected to reduce bank-specific stock price crash risk.

Hypothesis 1: Credit information sharing is expected to reduce bank-specific stock price crash risk.

4.2.3 Credit Information Sharing, Information Asymmetry and Stock Price Crash Risk

As documented in the previous section, the lack of bank's transparency motivates managerial incentive to hoard bad news leading to stock price crash risk. Nevertheless, in countries with a more transparent information environment, both financial and non-financial firm-level information tends to be released in a more accurate and timely manner. In an environment with less transparent information environment, credit information sharing among banks should be particularly more useful for banks, since bank relationship managers as well as investors may not be able to obtain much information directly from their borrowers/firms of interest. In such an environment, bank loan officers have more ability to hoard bad news resulting in the misperception of investors toward the true underlying performance of banks. Thus, we expect that the benefits of credit information sharing on stock price crash risk are likely to be more (less) pronounced in less (more) transparent information environment. To test our prediction, we employ two variables to proxy for the overall country-level information environment, which have been used earlier in this thesis. These proxies are International Financial Reporting Standards (IFRS) adoption and the Business Extent of Disclosure index (BDI).

According to our first variable, we use a country-level mandatory adoption of IFRS to proxy for a transparency of information environment. Previous research find that IFRS adoption has favorable consequences on capital market, including increasing liquidity, reducing the cost of capital, increasing firm's information environments, and improve financial reporting comparability across firms (Daske *et al.* 2008; Li 2010; Byard *et al.* 2011; DeFond *et al.* 2011; Tan *et al.* 2011). Proponents of IFRS adoption argue that increased reporting transparency enables investors to more easily compare financial performance across different jurisdictions (Daske *et al.* 2008; DeFond *et al.* 2014). Thus, IFRS adoption is expected to enhance the transparency of information environment primarily through additional disclosure and improved comparability, which in turn expected to increase overall transparency.

Since firms (borrowers) are more transparent and easily comparable to their peers when IFRS adoption is mandatory in a country, much more information about the firms can be discovered directly. The credit bureaus that shared among banks are thus less useful to the relationship managers and the bank loan officers have less ability to hide bad news about firms' prospect. In this regard, we expect that IFRS adoption would improve firms' transparency and comparability which could in turn affect the relationship between credit information sharing and stock price crash risk. Specifically, we hypothesize that the impact of credit information sharing on bank-specific stock price crash risk is less pronounced in countries with mandatory IFRS adoption.

Second, we use another country-level index to proxy for the information environment. That measurement is BDI taken from the World Bank's Doing Business. This index measures the extent to which investors are protected through disclosure of ownership and financial information (World Bank's Doing Business 2016). Particularly, BDI measures how well are minority shareholders protected from disclosure of transactions that involve conflicts of interests by controlling shareholders. The index ranges from 0 to 10 with higher value indicating more disclosure of ownership and financial information. When the level of BDI is low, the information environment is likely to be less transparent and the controlling shareholders is likely to expropriate minority shareholders and creditors.

In general, expropriation is related to the agency problem described by Jensen and Meckling (1979), who focus on the consumption of "Perk" by managers and other types of empire building. When the transaction involving conflict of interest is not transparent, the insiders have an incentive and ability to expropriate the profits of the firm to benefit themselves rather than return the money to the outside investors (La Porta *et al.* 2000). Expropriation can take various forms. For example, the profits are simply stolen by the insiders. In some circumstance, the insiders may sell the assets, the output, or the additional securities in the firm they control (Seller) to another firm they own (Buyer) at below market prices. Though often legal, such asset stripping[25], investor dilution[26], and transfer pricing[27] have largely the same effect as theft (La Porta *et al.* 2000). In addition, there are some other forms of expropriation; for instance, placing possibly unqualified family members in

[25] The practice of taking over a company in financial difficulties and selling each of its assets separately at a profit without regard for the company's future.
[26] It is when a company issues additional shares, this reduces an existing investor's proportional ownership in that company.
[27] The setting of the price of goods and services sold between controlled (or related) legal entities within the enterprise. For example, if a subsidiary company sells goods to a parent company, the cost of those goods paid by the parent to the subsidiary is the transfer price.

managerial positions, deviating corporate opportunities from the firm, or paying executives too much.

Thus, with less disclosure of ownership and financial information, banks become less transparent and control shareholders are likely to expropriate. Moreover, when banks are less transparent, loan officers can report to their boss in a favor of their careers about their assigned borrowers' prospect. Furthermore, the boss of loan officers and investors cannot directly obtain much information from borrowers of interest when the overall information environment is less transparent; therefore, their knowledge about borrowers relies on the reports of loan officers as well as credit bureaus. Taken together, we expect the relationship between credit information sharing and stock price crash risk to vary with both the mandatory adoption of IFRS and the extent of BDI. Specifically, we hypothesize that the relationship between credit information sharing and stock price crash risk is less pronounced with mandatory IFRS adoption and high business extent of disclosure index.

Hypothesis 2: The impact of credit information sharing on bank-specific stock price crash risk is expected to be less pronounced when the information environment is more transparent (as proxied by IFRS adoption and BDI).

4.2.4 Credit Information Sharing, Bank Regulations and Stock Price Crash Risk

Banks play a major role in the functioning of economic systems (Beck *et al.* 2000; Levine 2004; Demirgüç-Kunt *et al.* 2012). Specifically, banks are responsible for safeguarding deposits' rights, guaranteeing the stability of the payment system and reducing systemic risk (De Andres & Vallelado 2008). Moreover, they are highly leveraged as they take deposits from customers. Due to the nature of the banking business, banks are more opaque and complex than other firms (Furfine 2001; Morgan 2002; Flannery *et al.* 2004; Levine 2004). As a result, the poor governance of banks can lead to banking crises crippling economies, destabilizing governments and intensifying poverty (Barth *et al.* 2013b; Fernández *et al.* 2013; Fernández *et al.* 2016). That is why well-functioning banking systems are crucial for economic growth and development (Levine 1997, 2005). Therefore, banks are heavily regulated (Levine 2004).

Regulation and supervision are considered as an additional external governance force that acts macro-economically at the banking industry level as a whole and micro-economically at the individual bank level (Ciancanelli & Reyes-Gonzalez 2000; Macey & O'hara 2003; Arun & Turner 2004; Barth *et al.* 2006; Beck *et al.* 2006b; De Andres & Vallelado 2008). If bank managers face sound governance mechanisms, they will be more likely to allocate capital efficiently. In contrast, if bank managers enjoy enormous discretion to act in their own interests rather than in the interests of shareholders and debt holders, then banks will be correspondingly less likely to allocate society's savings efficiently and may have more ability to conceal their bad behaviors. Inefficiency of capital allocation can lead to the likelihood of bank failures and thereby curtail corporate finance and economic development (Levine 2004).

In general, there are two contradicting theoretical views about the effects of bank regulation and supervision on corporate governance of banks. Two opposing views point to the public interest and private interest. On one hand, according to the "public interest view", the regulators/supervisors act in the interests of the public and regulate banks to enhance banking efficiency and eliminate market failures due to market imperfection. Particularly, this view suggests that regulators/supervisors have the capabilities to eliminate market failures by directly monitoring and regulating banks. By doing so, intense regulation and strong supervision can enhance corporate governance of banks, reduce corruption in lending, improve the efficiency of capital allocation, encourage competition and hence boost the efficiency of banking sectors (Stigler 1971; Beck *et al.* 2006b). Thus, according to this view, banks in a stringent regulatory environment will carefully channel credits to profitable investments and there is less opportunity for their loan officers to hide their poor performance or any bad news that could lead to crash risk.

On the other hand, the "private interest view" argues that regulators/supervisors do not maximize social welfare, but they maximize their own welfare and may not have incentives to fix market failures (Rossiter *et al.* 1961; Buchanan & Tullock 1962; Becker 1983; Shleifer & Vishny 1998; Djankov *et al.* 2002; Quintyn & Taylor 2003). Their regulation and supervision are often used to promote the special interests of the few, not the broader public. Therefore, if they have the power to discipline non-compliant banks, then they will rather use the regulation and their privileged positions to channel credit to special interest groups, such as politically connected firms (Stigler 1971; Becker & Stigler 1974).

Under this condition, banks do not allocate based on risk-return criteria but their distribution of bank credit is influenced by corruption and political ties. This view suggests that powerful supervision and regulation tend to reduce the integrity of lending which leads to more lending corruption and increased likelihood of bad news hoarding activities.

With these two opposing views, the effectiveness of regulation and supervision therefore depends crucially on whether which force dominates the other. The regulations will serve as an additional external governance for banks if the public interest views were to dominate the private interest views. According to the underlying objective and design of bank regulations for improving public welfare, we expect the impact of credit information sharing on crash risk to be less pronounced with intense regulation and powerful supervision.

Existing theoretical and empirical literature suggests that the effectiveness of bank regulation and supervision varies with the type of regulations under study (Barth *et al.* 2006; Barth *et al.* 2013a; Barth *et al.* 2013b). Therefore, we separately analyze three aspects of bank regulation and supervision related to the three pillars of the Basel Accords, namely capital adequacy, official supervisory power and market discipline. The Basel Accords are three sets of banking regulations (Basel I, II and III) issued by the Basel Committee on Bank Supervision (BCBS)[28], which provides recommendations on banking regulations regarding capital risk, market risk, and operational risk. The Basel Accords are established to ensure that financial institutions have enough capital on account to meet obligations and absorb unexpected losses.

4.2.4.1 Capital Regulation

On the theoretical side, traditional approaches to bank regulation suggest a positive impact of capital adequacy on bank performance and efficiency which is being driven by reduced moral hazard between shareholders and debt holders (Kim & Santomero 1988; Berger *et al.* 1995; Barth *et al.* 2006; Allen *et al.* 2011). Capital can serve as a buffer against losses and prevent failure (Allen *et al.* 2011). Regulation on capital adequacy requires the

[28] The BCBS was founded in 1974 as a forum for regular cooperation between its member countries on banking supervisory matters. The BCBS describes its original aim as the enhancement of "financial stability by improving supervisory knowhow and the quality of banking supervision worldwide." Later on, it turned its attention to monitoring and ensuring the capital adequacy of banks and the banking system.

amount of capital that banks need to set aside for potential risk (Allen & Gale 2000; Allen *et al.* 2011). If bank owners are required to set aside more capital, then the upside gains from greater risk-taking would be compensated by the potential downside loss of their capital (Kim & Santomero 1988; Berger *et al.* 1995; Allen *et al.* 2011). By putting bank equity at risk, capital requirements reduce gambling incentives (excessive risk-taking) and promote prudent behavior (Hellmann *et al.* 2000). Thus, capital adequacy regulations are believed to play an important role in aligning the incentives of bank owners with depositors and other creditors. In particular, a higher capital level can increase shareholders' incentive to control risk and hence improving monitoring incentives (Berger *et al.* 1995). So, capital ratios induce banks to be more careful in lending and involve less risk-taking behaviors, especially excessive risk-taking (Keeley & Furlong 1990; Kaufman 1992; Barth *et al.* 2006; Mehran & Thakor 2011). With more stringent capital regulation, banks have an incentive to liquidate bad projects promptly and take early actions on bad loans. In comparison, banks with the less stringent capital requirement are likely to be less disciplined and tend to involve in more lending corruption than those with more capital requirement. Thus, we expect to see the impact of credit information sharing on crash risk to be more pronounced for banks in a bank regulatory environment with less stringent capital regulation.

However, capital regulations might increase banks' risk-taking behaviors (Koehn & Santomero 1980; Buser *et al.* 1981; Kim & Santomero 1988; Besanko & Kanatas 1996; Blum 1999). As argued by Koehn and Santomero (1980) and Buser, Chen, and Kane, (1981), if stringent capital requirement reduces a bank's value, bank owners may have an incentive to gamble and pursue riskier investment portfolio to compensate for the loss of utility, intensifying conflicts between owners and managers over bank risk taking. Hence, there is a no theoretical consensus on the effect of capital requirements on bank tendency to behave prudently. Nonetheless, our hypothesis is based on the underlying objective and design of capital adequacy regulation that enhances banks' corporate governance and limit their risk-taking behaviors.

Hypothesis 3-A: The impact of credit information sharing on bank-specific stock price crash risk is expected to be more pronounced in a banking regulatory environment with less stringent capital regulation.

4.2.4.2 Official Supervisory Power

The Basel Committee, International Monetary Fund, and World Bank stresses the importance of supervisory quality and independence in monitoring and disciplining banks (Beck *et al.* 2006b). However, there are conflicting views about the benefits of strong supervision. On the one hand, as discussed early, bank supervisors have the incentive and expertise to overcome market imperfection. In this regards, some theoretical models argue that supervisors need significant powers to prevent banks from engaging in undesirable activities and from taking excessive risks, especially in light of the growing complexity of banking activities (Stigler 1971; Beck *et al.* 2006b). Therefore, strong and powerful supervisory agency is needed to enhance the bank corporate governance by directly monitoring and disciplining.

On the other hand, opponents argue that bank supervisors will not focus on overcoming market failures but will focus on their private interests/welfare; therefore, giving supervisors more power fosters corruption (Rossiter *et al.* 1961; Buchanan & Tullock 1962; Becker 1983; Shleifer & Vishny 1998; Djankov *et al.* 2002; Quintyn & Taylor 2003). Under this view, supervisors can use their power to extract favors from banks in the form of loans, bribes or donations for their own benefit or their entourage rather than seeking to improve public welfare. Powerful supervisors may also push banks to make a sub-optimal lending decision which reduces bank performance and efficiency. Under this condition, banks do not allocate loans based on risk-return criteria but the distribution of loans is influenced by corruption and political ties. Thus, this view suggests that powerful supervisory agencies tend to reduce the integrity of lending that leads to more lending corruption and impedes banking efficiency. Rather than focusing on the political influence of supervisors, when there is uncertainty about the supervisor's ability to monitor banks' asset choice, supervisors may pursue self-interest to gain reputation rather than social welfare (Boot & Thakor 1993). As argued by Boot and Thakor (1993), a self-interested supervisor may undertake socially sub-optimal actions that distort banks closure policy and raise the liability of the deposit insurance fund leading. Although these two views are contradicted to each other, our hypothesis is based on the underlying objective and design of giving supervisors the power to improve the public welfare.

Hypothesis 3-B: The impact of credit information sharing on bank-specific stock price crash risk is expected to be more pronounced in a banking regulatory environment with low supervisory power.

4.2.4.3 Private Monitoring (Market-based monitoring)

Private monitoring refers to the disclosure of information to officials, the public and specialized entities such as rating agencies and auditors. Promoting market discipline recognizes both the public interest view, which encourages the intervention of regulators/supervisors to fix market failure and the private interest view, which argue that supervisory agencies have an incentive to serve their own interest but not to ease market failure. This view of recognition refers to "private empowerment" (Hay & Shleifer 1998). As argued in Beck *et al.* (2006b), bank supervisory policies should focus on inducing banks to disclose accurate information to the public in order to enhance the ability and incentives of private agents/investors to overcome informational barriers and transaction costs. Consequently, private agents/investors can exert effective monitoring and governance over banks.

Since regulators/supervisors do not have an ownership stake in banks, so they have different incentives than private creditors when it comes to monitoring and disciplining banks (Barth *et al.* 2004, 2006). Bank shareholders and creditors have a greater incentive to monitor banks than regulators because of their on-going ownership and lending relationships (Levine 2005). In addition, banks might use power to excessively pressure politicians to influence regulators/supervisors to serve mainly the special interests of the banks (Shleifer & Vishny 1998). Thus, the heavy emphasis placed on official supervision of banks is questionable and it is important to place a greater reliance on market discipline to promote better functioning banks. However, excessively heavy reliance on private monitoring may not always be efficient. As argued in (Barth *et al.* 2004), private monitoring may not be effective in countries with a poorly developed capital market and legal system. In addition, the complexity of banks, especially in developed countries, may make it difficult for private sectors to monitor. In line with the argument above, we expect to see that market monitoring would affect the relationship between credit information sharing and stock price crash risk.

Hypothesis 3-C: The impact of credit information sharing on bank-specific stock price crash risk is expected to be more pronounced in a banking regulatory environment with low degree of market monitoring.

4.3 Data and Methodology

4.3.1 Data

4.3.1.1 Data Source and Sample

Our sample covers 1,402 listed banks in 55 countries during the period 2005 – 2013. For data in the year 2005, we only use it to construct all explanatory and control variables for predicting the dependent variable in the year 2006. We compile data from several different sources. To construct crash risk measures, we obtain data on stock return from *Datastream (Thomson Reuters)* and supplement with the *Bankscope Database*.

Similar to previous two chapters, we take data on credit information sharing and the business extent of disclosure index (BDI) from the *World Bank's Doing Business Database.* Data on IFRS adoption are taken from the *IFRS Foundation website*, *Deloitte* and *Simon Fraser University in Canada*. Other data are obtained from the *World Bank's World Development Indicators (WDI) Database*, the *World Bank's World Governance Indicators (WGI)*, the *World Bank's Bank Regulation & Supervision Survey Database,* the *Deposit Insurance Database*, the *Central Intelligence Agency (CIA)* and the dataset from *Easterly (2001)*, *La Porta et al. (1999)* and *Djankov et al. (2007)*. Further descriptions and links to data sources can be found in Appendix A.

4.3.1.2 Variable Measurement

4.3.1.2.1 Dependent Variable

Following Chen *et al.* (2001) and Hutton *et al.* (2009), we define crash risk as the occurrence of negatively extreme firm-specific weekly returns and the conditional skewness of return distribution. Conditional skewness, like mean and median, is an important characteristic of the return distribution. Unlike prior studies that focus on stock performance and firm risk, which capture the mean (first moment) and variance (second moment) of return distribution, identifying crash risk focuses on conditional skewness, which is the third moment of the return distribution. Crash risk captures asymmetry in risk, especially downside risk, so it is important for investment decisions and risk management (Chen *et al.* 2001; Kim *et al.* 2014).

To examine the relationship between credit information sharing and future stock price crash risk, we construct two measures of asymmetry in stock-return that are commonly used in measuring crash likelihood in the crash risk literature. These variables are a negative conditional skewness (*NCSKEW*) and a Down-to-Up Volatility (*DUVOL*). They capture different aspects of the relative size and magnitude of stock price crash (Andreou *et al.* 2015). Prior studies (Hutton *et al.* 2009; Kim *et al.* 2011b, a; Kim *et al.* 2014; An *et al.* 2015) also use these two indicators to measure stock price crash risk. This method ensures that the stock price crash risk can reflect firm-specific factors rather than broad market movements.

To start constructing the two measures of crash risk, we initially need to calculate weekly stock returns. We collect the total return index (RI code) from Datastream and deal with RI as suggested by Ince and Porter (2006) and other previous studies (Jin & Myers 2006; Hutton *et al.* 2009; Kim *et al.* 2011a; An *et al.* 2015) on constructing crash risk. Similar to their construction, if RI is less than 0.01, then we set RI to be missing because Datastream rounds RI to the nearest tenth, which could exaggerate the proportion of zero-return. In addition, we delete an observation if the weekly stock return (Ret) is above 200% and reverses within one week, and truncate the absolute value of Ret at 0.5 for unusually large weekly returns.

Following the previous literature (Hutton *et al.* 2009; An *et al.* 2015), we apply standard filters to remove firm-year observations according to the following criteria:

- If there are fewer than 26 weekly stock returns available in a firm-year,
- If a firm is considered as American Depository Receipts (ADRs) or Global Depository Receipts (GDRs).

- Last, all variables are winsorized at the 1st and 99th percentiles.

Next, we need to estimate the firm-specific weekly returns for each firm and year. Using firm-specific returns ensures that our crash risk measures reflect firm-specific factors rather than broad market movements (Kim *et al.* 2014). Specifically, we obtain the firm-specific weekly return based on the residual return estimated from the expanded market model as follows:

$$\begin{aligned} r_{i,t} = \alpha_i &+ \beta_{1,i} r_{m,j,t} + \beta_{2,i}\left[r_{U.S.,t} + EX_{j,t}\right] + \beta_{3,i} r_{m,j,t-1} + \beta_{4,i}\left[r_{U.S.,t-1} + EX_{j,t-1}\right] \\ &+ \beta_{5,i} r_{m,j,t-2} + \beta_{6,i}\left[r_{U.S.,t-2} + EX_{j,t-2}\right] + \beta_{7,i} r_{m,j,t+1} \\ &+ \beta_{8,i}\left[r_{U.S.,t+1} + EX_{j,t+1}\right] + \beta_{9,i} r_{m,j,t+2} + \beta_{10,i}\left[r_{U.S.,t+2} + EX_{j,t+2}\right] \\ &+ \varepsilon_{i,t} \end{aligned} \tag{4-1}$$

Where $r_{i,t}$ is the stock return for firm i in week t, $r_{m,j,t}$ is the local market return for country j in week t, $r_{U.S.,t}$ is the U.S. market return in week t (a proxy global market return), and $EX_{j,t}$ is the change in exchange rate for the currency of country j against the U.S. dollar in week t. We incorporate two lead and lag terms for the local and U.S. market index return to allow (correct) for nonsynchronous trading (Dimson 1979).

The firm-specific weekly return for firm i in week t, ($W_{i,t}$), is measured by the natural logarithm of one plus the residual return from Equation (4-1), that is, $W_{i,t} = \log(1 + \varepsilon_{i,t})$. We transform in such a way because the residuals ($\varepsilon_{i,t}$) from Equation (4-1) are highly skewed; as a result of transformation, they become a roughly symmetric distribution, even in the tails, which is our greatest concern. This transformation allows us to define crash and positive jumps symmetrically. Moreover, using actual returns rather than residuals would result in an abundance of crashes during broad market declines and jumps during advances. After we obtain firm-specific weekly returns $W_{i,t}$, then we are able to construct two measures of crash risk accordingly.

The first crash risk measure is the negative conditional skewness of firm-specific weekly returns over a fiscal year ($NCSKEW$). Specifically, $NCSKEW$ for a given firm in each year is calculated by taking the negative of the third moment of firm-specific weekly returns for each sample year and dividing (normalizing) it by the standard deviation of firm-specific weekly returns raised to the third power (Chen *et al.* 2001; Kim *et al.* 2011b). Specifically, for each firm i in a year, $NCSKEW$ is computed as follows:

$$NCSKEW_{i,t} = -\left[n(n-1)^{3/2}\sum W_{i,t}^{3}\right]\Big/\left[(n-1)(n-2)\left(\sum W_{i,t}^{2}\right)^{3/2}\right] \quad (4\text{-}2)$$

Where $W_{i,t}$ is firm-specific weekly return as defined above, and n is the number of weekly return observation of year t. The reason we scale the raw third moment by the standard deviation cubed allows for comparisons across stocks with different variances (Chen *et al.* 2001); this is an usual way of normalizing skewness statistics (Greene 2003). We put the negative sign in front of the third moment in order to show that a higher value of $NCSKEW$ indicates higher crash risk i.e. having a more left-skewed distribution. As some option and asset pricing applications require future skewness as an input, building a model that predicts skewness could therefore contribute to this line of research (Hutton *et al.* 2009; Kim & Zhang 2015).

As a robustness test, the second crash risk measure is the down-to-up volatility measure of the crash likelihood ($DUVOL$). For each firm i over a fiscal year, firm-specific weekly returns are classified into two groups, "down" and "up". The first group with "Down" weeks consists of the returns that are below the yearly mean and the second group with "Up" weeks consists of the returns that are above the yearly mean. The standard deviation of firm-specific weekly returns is estimated separately for each of these two groups, and the volatility of down-to-up is calculated by taking the natural logarithm of the ratio of the standard deviation of the group with "down" weeks to the standard deviation of the group with "up" weeks as shown below:

$$DUVOL_{i,t} = log\left[(n_u - 1)\sum_{DOWN} W_{i_d,t}^{2}\Big/(n_d - 1)\sum_{UP} W_{i_u,t}^{2}\right] \quad (4\text{-}3)$$

Where $W_{i_d,t}$ and $W_{i_u,t}$ are the firm-specific returns for down-weeks and up-weeks, respectively; n_u and n_d are the numbers of up- and down- weeks in year t, respectively. A higher value of $DUVOL$ is associated with higher level of crash risk.

4.3.1.2.2 Explanatory Variables

Credit Information Sharing Proxy

In this chapter, we also rely on the depth of credit information sharing index ($DEPTH_{t-1}$) to measure the scope, accessibility, and quality of credit information available through private credit bureaus and public credit registries. The detail of the depth of credit information sharing index can be found in Table 4-1. In addition to the depth of credit information sharing, we also isolate the impact of private credit bureaus and public credit registries due to the differences between private and public credit registries.

The major difference between private credit bureaus and public credit registries is that participation in a public credit registry is compulsory to all banks in a country imposed by regulation. Also, public credit registries are managed by the public sector, usually by the central bank or banking supervisors. Unlike private credit bureaus, the development of public credit registries coincides with the banking regulatory and supervisory motivation (Majnoni *et al.* 2004). Thus, the coverage of public credit registries is usually larger than the coverage of private credit bureaus (Jappelli & Pagano 2002). However, although private credit bureaus are less comprehensive in coverage, they offer details on individual loans and combine credit data with other data sources such as leasing and finance companies, retail establishment, courts tax authorities (Miller 2003). In contrast, public credit registries provide merely credit data and the data is disseminated in consolidated form, so the information about individual loans is not available[29]. Furthermore, public credit registries usually set a minimum loan size and so collect information only on loans in excess of that minimum amount (Miller 2003). In addition, the data on public credit registries is only collected from banks and, in most cases, historical data are not made available through the public credit registries (Miller 2003). Due to these differences, it is worthwhile to examine whether private credit bureaus and public credit registries have different impacts on bank-specific stock price crash risk.

To isolate the impact of private credit bureaus and public credit registries, we use the

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[29] The total credit exposure of a borrower is often aggregated due to confidentiality concerns. Also, the names of the lending institutions are omitted before the data is distributed to others.

coverage of private bureaus ($PRIV_{t-1}$) and public registries (PUB_{t-1}) , to proxy for the information content of the information agencies. They are taken from the World Bank's Doing Business database. The private bureau coverage is defined as the number of individuals and firms listed in a private credit bureau with information on repayment history, unpaid debts, or credit outstanding from the past five years scaled by adult population (the population age 15 and above according to the WDI database). Similarly, the public registry coverage is defined as the number of individuals and firms listed in a public credit registry with information on repayment history, unpaid debts, or credit outstanding from the past five years scaled by adult population (the population age 15 and above according to the WDI database).

Information Environment Proxy

To proxy for the transparency of information environment, we follow the previous two chapters by employing the IFRS dummy and the Business Extent of Disclosure Index (BDI). The IFRS dummy is a dummy variable whose value is equal to one if a country (and year) mandatorily adopt IFRS and zero otherwise. The value of one indicates that the information environment is more transparent. The list of countries with mandatory IFRS adoption is in Appendix B. For BDI, we assign a dummy variable equal to 1 for a country with a value of BDI lower than the sample 50th percentile and zero for those above the sample 50th percentile. We name this dummy "LOW_BDI". Thus, a LOW_BDI whose value equal to one (zero) indicates that the information environment is less (more) transparent. More detail of the components of BDI can be found in Appendix C.

Banking Regulation Variables

We analyze three aspects of bank regulation related to the three pillars of the Basel Accords (Basel I, II, and III). Those pillars are capital adequacy, official supervisory power, market discipline. The first variable is *Capital Stringency index*, which is related to regulation on capital adequacy (Pillar 1). This variable is an index measuring the extent of both initial and overall capital stringency. It is constructed from several variables that indicate whether the capital requirement reflects certain risk elements and deducts certain market value losses from capital adequacy is determined. This variable is constructed by adding 1 if the answer is yes and 0 otherwise, for each one of the following fourteen questions:

1. Whether the minimum capital-asset ratio requirement is in line with the Basel Committee on Banking Supervision guidelines
2. Does the minimum ratio varies as a function of an individual bank's credit risk?
3. Does the minimum ratio varies as a function of an individual bank's market risk?
4. Before minimum capital adequacy is determined, which of the following are deducted from the book value of capital:
    a. Market value of loan losses not realized in accounting books?
    b. Unrealized losses in securities portfolios?
    c. Unrealized foreign exchange losses?
5. What fraction of revaluation gains is allowed as part of capital? (1 if the fraction is less than 0.75 and 0 otherwise)
6. Are the sources of funds to be used as capital verified by the regulatory/supervisory authorities?
7. Can the initial disbursement or subsequent injections of capital be done with assets other than cash or government securities?
8. Can initial capital contributions by prospective shareholders be in the form of borrowed funds?

The capital stringency index ranges from 0 to 10. Lower (higher) index indicates lower (higher) capital stringency. We assign a dummy variable equal to 1 for a country with a value of capital stringency index lower than the sample 50th percentile and zero for those above the sample 50th percentile. We name this dummy *LOW_CAPITAL_STR*. Thus, a

LOW_CAPITAL_STR whose value equal to one (zero) represents a group with low (high) capital stringency indices.

The second variable is *Official Supervisory Power index*. This variable is an index measuring the power of supervisors in direct regulating and monitoring banks in each country. In general, powerful official supervisors could improve the governance of banks and promote competition (Levine 2003). A strong and independent supervisor would be able to prevent managers from engaging in an excessive risk-taking behavior. This variable is constructed by adding 1 if the answer is yes and 0 otherwise, for each one of the following fourteen questions:

1. Does the supervisory agency have the right to meet with external auditors to discuss their report without the approval of the bank?
2. Are auditors required by law to communicate directly to the supervisory agency any presumed involvement of bank directors or senior managers in illicit activities, fraud, or insider abuse?
3. Can supervisors take legal action against external auditors for negligence?
4. Can the supervisory authority force a bank to change its internal organizational structure?
5. Are off-balance sheet items disclosed to supervisors?
6. Can the supervisory agency order the bank's directors or management to constitute provisions to cover actual or potential losses?
7. Can the supervisory agency suspend the directors' decision to distribute:
    a. Dividends?
    b. Bonuses?
    c. Management fees?

8. Can the supervisory agency legally declare – such that this declaration supersedes the rights of bank shareholders – that a bank is insolvent?

9. Does the Banking Law give authority to the supervisory agency to intervene, that is, suspend some or all ownership rights of a problem bank?

10. Regarding bank restructuring and reorganization, can the supervisory agency or any other government agency do the following:

    a. Supersede shareholder rights?

    b. Remove and replace management?

    c. Remove and replace directors?

The supervisory power index ranges from 0 to 14. Lower (higher) index indicates lower (higher) supervisory power. We assign a dummy variable equal to 1 for a country with a value of supervisor power index lower than the sample 50^{th} percentile and zero for those above the sample 50^{th} percentile. We name this dummy *LOW_SUPER_POW*. Thus, a *LOW_SUPER_POW* whose value equal to one (zero) represents a group with low (high) supervisory power indices.

The third variable is *Private Monitoring Index*, which is related to enhanced market discipline by promoting higher bank transparency and disclosure requirements. Specifically, this index measures the extent of regulation and supervisory policies in shaping the incentives and ability of private investors to monitor and exert effective governance over banks. This variable is constructed by adding 1 if the answer is yes and 0 otherwise, for each one of the following fourteen questions:

1. Whether bank officials are legally liable if the information disclosure is erroneous or misleading?

2. Whether banks disclosure information such as:

a. Consolidated accounts covering all bank and any non-bank financial subsidiaries?

b. Off-balance sheet items?

c. Accrued, though unpaid interest/principal of non-performing loan?

d. Risk management procedures to the public?

3. Whether banks must be audited by certified international auditors?

4. Whether the largest ten banks are rated by international rating agencies?

5. Whether the largest ten banks are rated by domestic rating agencies?

6. Whether subordinated debt is allowable as part of capital?

7. Whether there is no explicit deposit insurance system and no insurance was paid the last time a bank failed?

The private monitoring index ranges from 0 to 10. Lower (higher) index indicates less (more) private monitoring. We assign a dummy variable equal to 1 for a country with a value of private monitoring index lower than the sample 50th percentile and zero for those above the sample 50th percentile. We name this dummy $LOW\_MONITOR$. Thus, a $LOW\_MONITOR$ whose value equal to one (zero) represents a group with low (high) private monitoring indices.

4.3.1.2.3 Control Variables

In accordance with previous literature, we include several control variables to isolate the effect of credit information sharing on crash risk. First, Chen *et al.* (2001) and Hong and Stein (2003) predicts that investor heterogeneity (the difference of opinions among investors) causes greater crash risk. Thus, we control for investor heterogeneity by using the detrended stock trading volume ($DTURN_{t-1}$) as a proxy as in Chen *et al.* (2001) and Hong and Stein (2003). The detrended stock trading volume (a change in stock trading volume) is calculated as the average monthly share turnover over the current year minus the average monthly share turnover over the previous year, where monthly share turnover is calculated as the monthly share trading volume divided by the total number of shares outstanding during the month. Chen *et al.* (2001) find that firms with high stock turnovers are more crash prone. Moreover, we control for stock volatility and past return. The stock volatility ($SIGMA_{t-1}$) is calculated as the standard deviation of firm-specific weekly stock returns over the past year. More volatile stocks are more likely to experience future stock price crashes (Chen *et al.* 2001). The past return (RET_{t-1}) is calculated as the arithmetic average of firm-specific weekly stock returns over the past year. This variable is a proxy for the level of stock market bubbles. Stocks with high past returns are also more likely to crash (Chen *et al.* 2001). Chen *et al.* (2001) argue that stocks with high past returns could show that a bubble has been building up, so these stocks could undergo a larger price drop when prices fall back to fundamentals (the bubble bursts).

Furthermore, following Hutton *et al.* (2009), we also include the standard control variables. First, we control for bank-size, calculated as the natural logarithm of the market value of equity in the past year (MV_{t-1}). A positive relationship between firm size and stock price crash has been documented in several studies (Harvey & Siddique 2000; Chen *et al.* 2001; Hutton *et al.* 2009). Second, we control for the market-to-book ratio ($MTBV_{t-1}$), calculated as the market value of equity divided by the book value of equity in the past year. Glamour or growth stocks (those with high $MTBV$) are more likely to experience future price crashes (Chen *et al.* 2001; Hutton *et al.* 2009). Third, we control for financial leverage (LEV_{t-1}), calculated as total liabilities divided by total assets. A higher leverage ratio indicates a higher financial risk, which can result in crash risk. However, high leverage can increase profitability and thus reduce crash risk. Hutton *et al.* (2009) show that financial leverage is negatively related to crash risk. Fourth, we control for bank profitability and operating performance (ROA_{t-1}), calculated as income before extraordinary items divided by lagged total assets. Hutton *et al.* (2009) also show that more effective operating performance is negatively associated with crash risk. Lastly, following Andreou *et al.* (2016), we include the capital ratio (CAP_{t-1}) as tier one risk-adjusted capital ratio and the bank's deposits over total assets (DEP_{t-1}).

To control for the differences in country-specific factors, we include gross domestic product per capita ($GDPC_{t-1}$), stock market capitalization ($MKTCAP_{t-1}$) and a growth rate of gross domestic product ($GDPG_{t-1}$). Specifically, first, $GDPC_{t-1}$ is the natural logarithm of gross domestic product per capita measured in US dollars. Second, $MKTCAP_{t-1}$ is the stock market capitalization scaled by gross domestic product. Lastly, $GDPG_{t-1}$ is an annual growth rate of the gross domestic product.

In the robustness tests, we incorporate six governance indexes from the WGI database. These indexes are control of corruption ($CORRUPTION_{t-1}$), government effectiveness (GOV_EFF_{t-1}), political stability and absence of violence/terrorism ($POLITIC_{t-1}$), regulatory quality (REG_QUA_{t-1}), rule of law ($RULE\_LAW_{t-1}$) and voice & accountability ($VOICE\_ACC_{t-1}$). Definition of all variables can be found in Table 4-1.

We also include conditional accounting conservatism of Khan and Watts (2009) as in Kim and Zhang (2015), Andreou *et al.* (2015) and Kousenidis *et al.* (2014). Accounting conservatism refers to the tendency of accountants to require a higher degree of verification to recognize good news as gains than to recognize bad news as losses (Basu 1997; Kim & Zhang 2015). This type of conservatism allows to counteract the tendency of managerial bad news withholding and speed up the announcement of good news in audited financial statements and reveal unverifiable unfavorable information (Watts 2003; LaFond & Watts 2008; Kothari *et al.* 2009; Ball *et al.* 2012; Hu *et al.* 2014). The faster recognition of bad news is usually termed news-dependent (or conditional) conservatism and, therefore, it is argued that conditional conservatism reduces the likelihood of a stock price crash (Hu *et al.* 2014; Kousenidis *et al.* 2014; Kim & Zhang 2015).

Following Khan and Watts (2009) on constructing conditional firm-year conservatism measure (C_SCORE_{t-1}), we first draw the Basu (1997) model, which measures asymmetric earnings timeliness, to estimate a firm-year measure of conservatism. The Basu (1997) yearly cross-sectional regression can be written as follows:

$$X_j = \beta_1 + \beta_2 D_j + \beta_{3j} R_j + \beta_{4j} D_j R_{jt} + \varepsilon_j \tag{4-4}$$

For firm j, where X_j is net income before extraordinary items scaled by the lagged market value of equity, R_j is annual returns compounded from monthly returns over the 12-month beginning of the fourth month after fiscal year end[30], D_j is a dummy equal to one if R_j is negative and zero otherwise, and ε_j is the error term. The timeliness of good news is represented by β_{3j}. The measure of incremental timeliness for recognizing bad news over good news (or conditional conservatism) is β_{4j}. More timely recognition of bad news in relation to good news is a sign of conservatism (Basu 1997).

Since the coefficients β_{3j} and β_{4j} in Basu (1997) regression are constant across firms, Khan and Watts (2009) take into variations in both firms and years by incorporating firm-specific characteristics into Equation (4-4). These firm's characteristics, including size, market-to-book, and leverage, are chosen because conservatism varies with them, both theoretically and empirically (LaFond & Watts 2008). Hence, the timeliness of good news each year (β_{3j}) and conditional conservatism each year (β_{4j}) are expressed as linear functions of firm-year specific characteristics that are correlated with the timeliness of good news and conditional conservatism each year, respectively. The equations can be written as follows:

$$G\_SCORE = \beta_{3j} = \mu_1 + \mu_2 MKV_j + \mu_3 MB_j + \mu_{4t} LEV_j \quad (4\text{-}5)$$

$$C\_SCORE = \beta_{4j} = \lambda_1 + \lambda_2 MKV_j + \lambda_3 MB_j + \lambda_4 LEV_j \quad (4\text{-}6)$$

Where μ_i and λ_i, i=1-4, are constant across firms but vary over time since they are to be estimated by yearly cross-sectional regression. Firm-specific characteristics are MKV_j, MB_j and LEV_j. MKV_j is the natural logarithm of the market value. MB_j is the ratio of the market to book value of equity and LEV_j is leverage defined as the ratio of debt to equity. Thus, G_SCORE and C_SCORE vary across firms through cross-sectional variation in the firm's characteristics (MKV, MB and LEV).

Equation (4-5) and Equation (4-6) are not regression models. Instead, they are substituted into Equation (4-4) to obtain Equation (4-7) below:

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[30] Annual returns are obtained by cumulating monthly returns starting from the fourth month after the firm's fiscal year end (Hyan, 1995; Basu, 1997; Khan and Watt, 2009.

$$
\begin{aligned}
X_{jt} = \beta_{1t} + \beta_{2t}D_{jt} + R_{jt}\big(\mu_{1t} + \mu_{2t}MKV_{jt} + \mu_{3t}MB_{jt} + \mu_{4t}LEV_{jt}\big) \\
+\ D_{jt}R_{jt}\big(\lambda_{1t} + \lambda_{2t}MKV_{jt} + \lambda_{3t}MB_{jt} + \lambda_{4t}LEV_{jt}\big) \\
+ \big(\delta_{1t}MKV_{jt} + \delta_{2t}MB_{jt} + \delta_{3t}LEV_{jt} + \delta_{4t}D_{jt}MKV_{jt} \\
+ \delta_{5t}D_{jt}MB_{jt} + \delta_{6t}D_{jt}LEV_{jt}\big) + \varepsilon_{jt}
\end{aligned}
\tag{4-7}
$$

Where the first bracket term is Equation (4-5) and the second bracket term is Equation (4-6). We include the third bracket term as an additional term in Equation (4-7) because, as explained by Khan and Watts (2009), the regression Equation (4-7) includes interaction terms between returns and firm-characteristics, so we have to also control for the firm characteristics separately (the "main effects").

As similar to Kim and Zhang (2015) and Kousenidis *et al.* (2014), instead of running yearly pooled cross-sectional regressions for each country, Equation (4-7) is estimated using five-year rolling panel regression for each country. Roychowdhury and Watts (2007) suggest that measuring the Basu (1997) conservatism metric using a longer horizon decrease the measurement error. In addition, the reason that we run the cross-sectional model for each country is due to cross country-level differences in financial reporting conservatism (Ball *et al.* 2008; Beatty *et al.* 2008). After the estimation of Equation (4-7), we calculate our conditional conservatism (C_SCORE or β_{4jt}) by substituting the estimators μ_{1t}, μ_{2t}, μ_{3t} and μ_{4t} from Equation (4-7) into Equation (4-6). By construction, banks with higher C_SCORE values are considered more conservative and thus they exhibit a smaller delay in expected loss recognition. Hence, it is a measure of asymmetric timeliness in recognizing bad news versus good news.

4.3.1.2.4 Summary Statistics

Table 4-1 summarizes all definitions and sources of variables as well as their symbols used in this chapter. Table 4-2 reports the descriptive statistics for the key variables along with control variables used in our multivariate analysis. All variables are winsorized at the 1% and 99% levels. Regarding the crash risk measures, the mean (median) value of negative conditional skewness (*NCSKEW)* is -0.0694 (-0.0384) and of a down-to-up volatility (*DUVOL)* is -0.0857 (-0.0777). In comparison to previous literatures on crash risk in the banking industry, our crash risk statistics are lower than those documented in Andreou *et al.*

(2016), which report -0.146 and -0.104 for *NCSKEW* and *DUVOL*, respectively. However, Andreou *et al.* (2016) focuses on U.S. banks, whereas we cover U.S. banks and other banks around the globe. Thus, the slight differences may be attributed to different samples as well as different timespan[31].

Regarding the credit information sharing measures, the mean (median) value of credit information depth (*DEPTH)* is 5.46 (5) and the mean values of private bureau coverage (*PRIV)* and public registry coverage (*PUB)* are 0.771 and 0.115, respectively. It is clear that the sample has very high depth of credit information sharing across banks and years. Moreover, the mean values of *PRIV* and *PUB* suggest that, on average, the coverage of private credit bureaus is approximately 77% of total adult population, while the coverage of public credit registries is approximately 11%. The coverage of public credit registries is considered low compared to the coverage of private credit bureaus. Regarding the banking regulatory variables, the mean values of the capital stringency index (*CAPITAL_STR*), the supervisory power index (*SUPER_POW*) and the private monitoring index (*MONITORING*) is 6.91, 9.36 and 7.17, respectively. Three mean values of banking regulatory variables are considerably high on average.

According to the control variables, the average change in monthly trading volume as a percentage of shares outstanding (*DTURN*) is -0.0652. The average bank in our sample has a firm-specific weekly return (*MEAN*) of -0.23%, a market capitalization (*MV*) of $327 million, a market-to-book ratio (*MTBV*) of 0.0278, and a weekly return volatility (*SIGMA*) of 0.0439. Moreover, as expected due to the nature of their operations, banks on average rely heavily on leverage with mean (*LEV*) of 0.909. They are also marginally profitable as captured by mean value of a return-on-asset ratio (*ROA*) of 0.005. Lastly, banks on average maintain a deposit-to-asset ratio (*DEPOSIT*) that equal to 0.72 and hold a tier 1 capital ratio (*CAR_TIER1*) that equal to 0.124. Regarding several country-level control variables, the GDP growth (*GDPG*) has a mean value of 2.03%, the stock market capitalization scaled by GDP (*MKTCAP*) has a mean value of 98.8% and a natural logarithm of GDP per capital (*GDPPC*) has a mean value of 10.4.

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[31] In some studies of crash risk of non-bank firms, the authors report slightly higher *NCSKEW* and *DUVOL* than ours (for example An and Zhang 2013 as well as An et al. 2015). Again, the differences may be due to different nature of a business, different samples and different timespans.

In addition to the variables used in the main regression, we also present the summary statistics of the following variables used either as additional controls or instrumental variables in robustness tests. The mean value of an accounting conservatism (*C_SCORE*) is 1.76. Regarding a series of political and institutional quality indexes, a control of corruption index (*CORRUPTION*) has a mean value of 1.12, a government effectiveness index (*GOV_EFF*) has a mean value of 1.31, a political stability index (*POLITIC*) has a mean value of 0.382, a regulatory quality index (*REG_QUA*) has a mean value of 1.19, a rule of law index (*RULE_LAW*) has a mean value of 1.28, and lastly a voice and accountability index (*VOICE_ACC*) has a mean value of 0.903.

In addition, we also report the descriptive statistics of main variables grouped by countries displayed in Panel A of Table 4-3. The average depth of credit information sharing across countries and year is 4.44 meaning that there is a significant number of countries that have information sharing institutions with high depth. Furthermore, the average coverage of private credit bureaus and public credit registries in each country are 41% and 11%, respectively. Panel B of Table 4-3 provides another descriptive statistics of variables used to construct *LOW_BDI, LOW_CAPITAL_STR, LOW_SUPER_POW* and *LOW_MONITOR*. Across the bank-year observations, the mean values of the business extent of disclosure index (*BDI*), the capital stringency index (*CAPITAL_STR*), the supervisory power index (*SUPER_POW*) and the private monitoring index (*MONITORING*) is 6.92, 6.91, 9.36 and 7.17, respectively. Three mean values of banking regulatory variables are considerably high on average. The mean of *BDI* is also high; however, by looking at the 25th percentile and 75th percentile of *BDI*, we can see that the sample has very little variation in *BDI* and clustered at the value of 7. However, we still try to employ although there is little variation in the values.

Table 4-4 presents the yearly sample distribution of our main variables. The table shows that the sample size is slightly more than 900 throughout our sample period 2006 to 2013. Note that all variables, except a measure of crash risk, are lagged by one year, so all variables in 2005 is used to predict crash risk in 2006 and so on. Our main crash risk measure, a negative conditional skewness (*NCSKEW)*, indicates a considerable variation across years, with 2008 having the highest crash risk, a reflection of the financial crisis. The average depth of credit information sharing (*DEPTH*) is considerably high across years. At the same time, the trend of private bureau coverage (*PRIV*) is downward whereas the trend of public registries coverage (*PUB*) is upward. On possible reason is that, more countries began to establish public credit registries, especially in developing and less developed countries. The average value of the business extent of disclosure index (*BDI*) is around 7 for every year. While the average supervisory power index (*SUPER_POW*) hoards around nine, the average capital stringency index (*CAPITAL_STR*) and private monitoring index (*MONITOR*) notably increase in 2009, especially private monitoring index. These increases indicate that bank regulation and supervision become more increasingly important since the financial crisis in 2008. In addition, the remark increase in the average *MONITOR* after the financial crisis reflects that regulators pay more attention to market monitoring mechanism and attempt to promote bank transparency through more public information disclosure.

We also check the correlation among stock price crash risk measures, credit information sharing measures, information environment measures, banking regulatory variables and other control variables. The matrix of Pearson correlation of all variables is presented in Table 4-5, Table 4-6 and Table 4-7. We find that multicollinearity is not a serious problem. Most of the correlation coefficients are below 0.3. The crash risk measure, $NCSKEW$, is positively correlated with *DEPTH* and *PRIV*, while it is negatively correlated with *PUB*. The correlation coefficient of *DEPTH* and *PRIV* is 0.7721, which is quite high. This highly positive correlation suggests that a country with the high depth of credit information tends to have high coverage of private credit bureaus or vice versa. However, each variable enters the regression individually, so the problem of multicollinearity should be less of a concern. Opposite to *PRIV*, *DEPTH* is negatively associated with *PUB*. Moreover, the governance variables (*CORRUPTION*, *GOV_EFF, POLITIC, REG_QUA,* $RULE\_LAW$*, VOICE_ACC*) exhibit a very strong correlation with one another; therefore, each enters the regression one at a time.

4.3.2 Methodology

To test our hypothesis H1, we estimate the following regression that links our crash risk measure in year t to credit information sharing measures in year $t-1$ and a set of control variables in year $t-1$:

$$CRASH_{i,t} = \beta_0 + \beta_1 CIS_{i,t-1} + \sum_{k=2}^{10} \beta_k (X_{i,t-1}^k) + \sum_{m=11}^{13} \beta_m (Y_{i,t-1}^m) + \lambda_t + \alpha_i + \varepsilon_{i,t} \quad (4\text{-}8)$$

Where i, t and t-1 indicates the i[th] bank, year t and year t-1, respectively; $CRASH_t$ is measured by $NCSKEW_t$, which is the negative skewness of firm-specific weekly returns; CIS_{t-1} is one of the three proxies of credit information sharing, namely the depth of credit information sharing ($DEPTH_{t-1}$), private bureau coverages ($PRIV_{t-1}$), and public registry coverages (PUB_{t-1}), measured in year $t-1$. *X* contains bank-specific variables, consisting of $DTURN_{t-1}$, $SIGMA_{t-1}$, $MEAN_{t-1}$, MV_{t-1}, $MTBV_{t-1}$, LEV_{t-1}, ROA_{t-1}, CAR_TIER1_{t-1} and $DEPOSIT_{t-1}$ as discussed in the data section. In addition, *Y* contains country-specific variables, consisting of $GDPG_{t-1}$, $MKTCAP_{t-1}$ and $GDPPC_{t-1}$ as discussed in the data section. λ_t is the year fixed effects; α_i is the individual effects or the time-invariant component of the error term; and *ε* is an idiosyncratic error term or time-varying component of the error term. Like previous literatures on crash risk, we impose a one-year lag between the dependent and independent variables to test whether *CIS* in year $t-1$ can predict crash risk in year t. Regarding to the hypothesis H1, the coefficient β_1 in front of CIS_{t-1} is expected to be negative and significant for all three proxies of credit information sharing so that bank-specific stock price crash risk is lower with more credit information sharing.

To test our hypothesis H2, which is whether the relationship between credit information sharing and stock price crash risk varies with a degree of information environment, we augment Equation (4-8) with one of the two proxies of information environment and their interactions with each of the three proxies of credit information sharing. The new regression model for Equation (4-8) is as followed:

$$\begin{aligned} CRASH_{i,t} = {} & \beta_0 + \beta_1 CIS_{i,t-1} + \beta_2 ASYM_{i,t-1} + \beta_3 ASYM_{i,t-1} * CIS_{i,t-1} \\ & + \sum_{k=4}^{12} \beta_k (X_{i,t-1}^k) + \sum_{m=13}^{15} \beta_m (Y_{i,t-1}^m) + \lambda_t + \alpha_i + \varepsilon_{i,t} \end{aligned} \quad (4\text{-}9)$$

Where i, t and t-1 indicates the i[th] bank, year t and year t-1, respectively; $CRASH_t$ is measured by $NCSKEW_t$, which is the negative skewness of firm-specific weekly returns; CIS_{t-1} is one of the three proxies of credit information sharing, namely the depth of credit information sharing ($DEPTH_{t-1}$), private bureau coverages ($PRIV_{t-1}$), and public registry coverages

(PUB_{t-1}), measured in year $t-1$; $ASYM_{t-1}$ is one of the two proxies of information environment, namely IFRS adoption ($IFRS_{t-1}$) and the business extent of disclosure index (LOW_BDI_{t-1}). X contains bank-specific variables, consisting of $DTURN_{t-1}$, $SIGMA_{t-1}$, $MEAN_{t-1}$, MV_{t-1}, $MTBV_{t-1}$, LEV_{t-1}, ROA_{t-1}, CAR_TIER1_{t-1} and $DEPOSIT_{t-1}$ as discussed in the data section. In addition, Y contains country-specific variables, consisting of $GDPG_{t-1}$, $MKTCAP_{t-1}$ and $GDPPC_{t-1}$ as discussed in the data section. λ_t is the year fixed effects; α_i is the individual effects or the time-invariant component of the error term; and ε is an idiosyncratic error term or time-varying component of the error term. The hypothesis H2 predicts the coefficient β_3 in front of the interaction term between $ASYM_{t-1}$ and CIS_{t-1} to be significantly positive for $IFRS_{t-1}$ and negative for LOW_BDI_{t-1} so that the impact of credit information sharing on stock price crash risk is less pronounced with mandatory IFRS adoption, while the impact is more pronounced with low BDI.

To test our hypothesis H3-A, which is whether the relationship between credit information sharing and stock price crash risk is affected by bank capital stringency, we augment Equation (4-8) with a $LOW\_CAPITAL\_STR$ dummy and its interaction with each of the three proxies of credit information sharing. The new regression model for Equation (4-8) is as followed:

$$\begin{aligned} CRASH_{i,t} = {} & \beta_0 + \beta_1 CIS_{i,t-1} + \beta_2 LOW\_CAPITAL\_STR_{i,t-1} \\ & + \beta_3 LOW\_CAPITAL\_STR_{i,t-1} * CIS_{i,t-1} + \sum_{k=4}^{12} \beta_k (X_{i,t-1}^{k}) \\ & + \sum_{m=13}^{15} \beta_m (Y_{i,t-1}^{m}) + \lambda_t + \alpha_i + \varepsilon_{i,t} \end{aligned} \tag{4-10}$$

Where i, t and t-1 indicates the ith bank, year t and year t-1, respectively; $CRASH_t$ is measured by $NCSKEW_t$, which is the negative skewness of firm-specific weekly returns; CIS_{t-1} is one of the three proxies of credit information sharing, namely the depth of credit information sharing ($DEPTH_{t-1}$), private bureau coverages ($PRIV_{t-1}$), and public registry coverages (PUB_{t-1}), measured in year $t-1$; $LOW\_CAPITAL\_STR_{t-1}$ is a dummy variable whose value equal to one indicating a group of low capital stringency indices. X contains bank-specific variables, consisting of $DTURN_{t-1}$, $SIGMA_{t-1}$, $MEAN_{t-1}$, MV_{t-1}, $MTBV_{t-1}$, LEV_{t-1}, ROA_{t-1}, CAR_TIER1_{t-1} and $DEPOSIT_{t-1}$ as discussed in the data section. In addition, Y contains country-specific variables, consisting of $GDPG_{t-1}$, $MKTCAP_{t-1}$ and $GDPPC_{t-1}$ as discussed in the data section. λ_t is the year fixed effects; α_i is the individual effects or the time-invariant component of the error term; and ε is an idiosyncratic error term or time-varying component of the error term. The hypothesis H3-A predicts the coefficient β_3 in front of the interaction term between $LOW\_CAPITAL\_STR_{t-1}$ and CIS_{t-1} to be negative and significant so that the impact of credit information sharing on stock price crash risk is more pronounced with low capital stringency.

To test our hypothesis H3-B, which is whether the relationship between credit information sharing and stock price crash risk is affected by a supervisory power of bank regulators, we augment Equation (4-8) with a LOW_SUPER_POW dummy and its interaction with each of the three proxies of credit information sharing. The new regression model for Equation (4-8) is as followed:

$$\begin{aligned} CRASH_{i,t} = \beta_0 + \beta_1 CIS_{i,t-1} + \beta_2 LOW\_SUPER\_POW_{i,t-1} \\ + \beta_3 LOW\_SUPER\_POW_{i,t-1} * CIS_{i,t-1} + \sum_{k=4}^{12} \beta_k (X_{i,t-1}^k) \\ + \sum_{m=13}^{15} \beta_m (Y_{i,t-1}^m) + \lambda_t + \alpha_i + \varepsilon_{i,t} \end{aligned} \tag{4-11}$$

Where i, t and t-1 indicates the i[th] bank, year t and year t-1, respectively; $CRASH_t$ is measured by $NCSKEW_t$, which is the negative skewness of firm-specific weekly returns; CIS_{t-1} is one of the three proxies of credit information sharing, namely the depth of credit information sharing ($DEPTH_{t-1}$), private bureau coverages ($PRIV_{t-1}$), and public registry coverages (PUB_{t-1}), measured in year $t-1$; $LOW\_SUPER\_POW_{t-1}$ is a dummy variable whose value equal to one indicating a group of low supervisory power indices. X contains bank-specific variables, consisting of $DTURN_{t-1}$, $SIGMA_{t-1}$, $MEAN_{t-1}$, MV_{t-1}, $MTBV_{t-1}$, LEV_{t-1}, ROA_{t-1}, CAR_TIER1_{t-1} and $DEPOSIT_{t-1}$ as discussed in the data section. In addition, Y contains country-specific variables, consisting of $GDPG_{t-1}$, $MKTCAP_{t-1}$ and $GDPPC_{t-1}$ as discussed in the data section. λ_t is the year fixed effects; α_i is the individual effects or the time-invariant component of the error term; and ε is an idiosyncratic error term or time-varying component of the error term. The hypothesis H3-B predicts the coefficient β_3 in front of the interaction term between $LOW\_SUPER\_POW_{t-1}$ and CIS_{t-1} to be negative and significant so that the impact of credit information sharing on stock price crash risk is more pronounced with low supervisory power.

To test our hypothesis H3-C, which is whether the relationship between credit information sharing and stock price crash risk is affected by a degree of private monitoring, we augment Equation (4-8) with a $LOW\_MONITOR$ dummy and its interaction with each of the three proxies of credit information sharing. The new regression model for Equation (4-8) is as followed:

$$\begin{aligned} CRASH_{i,t} &= \beta_0 + \beta_1 CIS_{i,t-1} + \beta_2 LOW\_MONITOR_{i,t-1} \\ &\quad + \beta_3 LOW\_MONITOR_{i,t-1} * CIS_{i,t-1} + \sum_{k=4}^{12} \beta_k (X_{i,t-1}^{k}) \\ &\quad + \sum_{m=13}^{15} \beta_m (Y_{i,t-1}^{m}) + \lambda_t + \alpha_i + \varepsilon_{i,t} \end{aligned} \tag{4-12}$$

Where i, t and t-1 indicates the ith bank, year t and year t-1, respectively; $CRASH_t$ is measured by $NCSKEW_t$, which is the negative skewness of firm-specific weekly returns; CIS_{t-1} is one of the three proxies of credit information sharing, namely the depth of credit information sharing ($DEPTH_{t-1}$), private bureau coverages ($PRIV_{t-1}$), and public registry coverages (PUB_{t-1}), measured in year $t-1$; $LOW\_MONITOR_{t-1}$ is a dummy variable whose value equal to one indicating a group of low private monitoring indices. *X* contains bank-specific variables, consisting of $DTURN_{t-1}$, $SIGMA_{t-1}$, $MEAN_{t-1}$, MV_{t-1}, $MTBV_{t-1}$, LEV_{t-1}, ROA_{t-1}, CAR_TIER1_{t-1} and $DEPOSIT_{t-1}$ as discussed in the data section. In addition, Y contains country-specific variables, consisting of $GDPG_{t-1}$, $MKTCAP_{t-1}$ and $GDPPC_{t-1}$ as discussed in the data section. λ_t is the year fixed effects; α_i is the individual effects or the time-invariant component of the error term; and ε is an idiosyncratic error term or time-varying component of the error term. The hypothesis H3-C predicts the coefficient β_3 in front of the interaction term between $LOW\_MONITOR_{t-1}$ and CIS_{t-1} to be negative and significant so that the impact of credit information sharing on stock price crash risk is more pronounced with low private monitoring.

In the robustness test, we re-estimate Equation (4-8) to Equation (4-12) with the following modifications and augmentations. Instead of $NCSKEW_t$, we measure $CRASH_t$ by

$DUVOL_t$, which is a down-to-up volatility measure of the crash likelihood as described in the data section. Furthermore, we add some more country-level controls related to political and institutional quality indices ($CORRUPTION_{t-1}$, GOV_EFF_{t-1}, $POLITIC_{t-1}$, REG_QUA_{t-1}, $RULE\_LAW_{t-1}$, $VOICE\_ACC_{t-1}$) and more bank-specific control indicating the degree of accounting conservatism (C_SCORE_{t-1}). In addition, we provide an instrumental variable regression by employing a legal origin dummy ($LEGALORIGIN_{t-1}$), ethnic fractionalization ($ETHNIC\_FRAC_{t-1}$) and latitude ($LATITUDE_{t-1}$) as instrumental variables for credit information sharing and stock price crash risk.

4.4 Empirical Results, Robustness Tests and Additional Tests

4.4.1 Empirical Results

4.4.1.1 The Impact of Credit Information Sharing on Stock Price Crash Risk

Table 4-8 shows the results of the model selection and diagnostic tests. We apply all tests to Equation (4-8) with no interaction terms. Afterward, we choose the estimation technique based on the tests and apply it to Equation (4-9), Equation (4-10), Equation (4-11) and Equation (4-12)[32]. Based on the results shown in Table 4-8, we prefer the fixed effect regression to the pool regression and the random effect regression. In addition, facing the problems of heteroscedasticity and serial correlation, we adjust standard errors that are robust to heteroscedasticity and cluster standard errors at bank-level to account for within-cluster correlation of the error term[33]

Table 4-9 shows the regression analysis for Equation (4-8) testing the relationship between credit information sharing and future bank-specific stock price crash risk. In Table 4-9, the coefficient estimates for Equation (4-8) with crash risk measured by *NCSKEW* are reported in column 1 to column 3. As shown in column 1, when *DEPTH*, that is, the depth of credit information sharing index, is used as our test variable, the coefficients of *DEPTH* is not significant. This insignificant relationship between the depth of credit information

[32] Adding interaction terms would not significantly change the overall results of the tests much.
[33] More detail of model selection tests and diagnostic tests can be found in the Appendix F.

sharing index and future crash risk is not consistent with our first hypothesis, suggesting that higher depth of credit information may not be sufficient to reduce crash risk.

Instead of the depth of credit information sharing, we rely on the private credit bureau coverages (*PRIV*) and the public credit registry coverages (*PUB*). As shown in the column 2 of Table 4-9, the coefficient of *PRIV* is not significant. However, in the column 3 of Table 4-9, the coefficient of *PUB* is highly significant (at 1% level) with an expected negative sign. The results show that only the relationship between information sharing through public credit registries and crash risk is significantly negative and consistent with our hypothesis H1. This significantly negative relationship between information sharing through public credit registries and crash risk suggests that banks are less likely to encounter crash risk in countries with more credit information sharing through public credit registries.

This finding is in line with the notion that forcing banks to share borrower information among each other may improve bank transparency and discourage their loan officers to withhold bad news for an extended period. Consequently, the accumulation of bad news less likely lead to a stock price crash. In more detail, compulsory information sharing can help monitoring loan officers and preventing corruption in lending. Also, borrower information sharing from one bank improves comparability and provides benefits to another bank validating internal risk ratings, so loan officers are less likely to bias their borrower reports. Therefore, forcing banks to disclose and share borrower information tends to improve investors' perception about banks' performance, such that it also reduces a stock price crash risk.

To assess the economic significance of the results, we estimate the marginal effect of credit information sharing on crash risk holding all other variables at their sample mean. First, regarding a one-percentage increase of *PUB*, we find that it corresponds to a 0.005 decrease in *NCSKEW*. Furthermore, we compare crash risk at the 10^{th} and 90^{th} percentile values of *PUB* and find that an increasing value of *PUB* from the 10^{th} to the 90^{th} percentile can additionally decrease *NCSKEW* by 0.028.

The insignificant impact of information sharing through private credit bureaus on future crash risk suggests that the voluntary exchange of credit information among banks may not be sufficient to prevent bad news hoarding. Banks may self-select themselves into sharing credit information and may share only information that makes them better off. Furthermore, joining the private credit bureaus is not compulsory and they are less regulated than the public credit registries (Majnoni *et al.* 2004). When less transparent banks are not obligated to share borrower information, they become lax in granting loans and their internal operations could become less disciplined. Thus, loan officers have the ability to hide bad prospects of their borrower that could affect their career performance.

According to the depth of credit information sharing, it does not differentiate between the depth of private credit bureaus and public credit registries. High depth index does not mean that high depth of information is being shared through private credit bureaus alone or public credit registries alone or both. However, as we can see from the correlation matrix (Table 4-5), the positive correlation between *PRIV* and *DEPTH* suggests that countries with high coverage of private credit bureaus tend to have a high depth of credit information sharing, while the correlation between *PUB* and *DEPTH* is negative and quite low. Therefore, high depth of information sharing among banks does not mitigate crash risk, possibly due to its highly positive correlation with the private bureau coverage.

The coefficients of the control variables for all regressions are generally consistent with the findings of prior studies. First, we find that the coefficient of *DTURN*, which proxies for investor belief heterogeneity, is significantly positive, consistent with the results of Chen *et al.* (2001). Furthermore, the coefficients of *SIGMA* are positive and significant, suggesting that banks that have a higher return volatility are associated with higher future crash risk. In addition, we find that the coefficient of *MV* is significantly positive, implying that large stocks are more crash prone. Moreover, the coefficient of *MTBV* is significantly negative, implying that growth stocks are less likely to crash. Consistent with Hutton *et al.* (2009), Kim *et al.* (2011b), Kim *et al.* (2011a) among others, the estimated coefficient of *ROA* is negatively and highly significant for all regressions, suggesting that banks with good operating performance are less likely to experience a crash. Lastly, we find that future crashes are positively related to *GDPPC,* suggesting that banks in richer countries are more crash prone.

4.4.1.2 The Impact of Information Asymmetry on the Relationship between Credit Information Sharing and Stock Price Crash Risk

Due to the regression results in the previous section, the only *PUB* is found to be significant. Therefore, in this section, we only use *PUB* to test our hypothesis H2. We hypothesize that the impact of *PUB* on stock price crash risk is less pronounced in countries with more transparent information environment. Table 4-10 presents the regression results for Equation (4-9). We proxy the transparency of the information environment by *IFRS* and *LOW_BDI*.

The *IFRS* dummy with the value of one equals the information environment that is more transparent than the *IFRS* dummy with the value of zero. As shown in column 2 of Table 4-10, the coefficient of the interaction term between *IFRS* and *PUB* is positive and significant. The positive coefficient of the interaction term indicates that the mandatory adoption of IFRS attenuates the impact of credit information sharing on stock price crash risk. In other words, the impact of credit information sharing on stock price crash risk is less pronounced in countries with more transparent information environment. When the information environment is more transparent, loan officers have less ability to hide negative information about borrowers because borrower information is abundantly assessable to external investors and loan managers.

We also evaluate the moderating effect of *IFRS* on the relationship between credit information sharing and crash risk. In countries with no mandatory IFRS adoption, a one-percentage increase of *PUB* will lead to a 0.009 decrease in *NCSKEW*. However, in countries with mandatory IFRS adoption, a one-percentage increase of *PUB* will lead to a 0.004 decrease in *NCSKEW*. The marginal effect shows that it is 0.005 or approximately 58.62% less pronounced with mandatory IFRS adoption. Thus, the beneficial effect of credit information sharing tends to be less helpful in reducing crash risk in the more transparent information environment.

Besides mandatory IFRS adoption, the result using *LOW_BDI* as a proxy of the transiency of the information environment is displayed in column 4 of Table 4-10. The coefficient of the interaction term between *LOW_BDI* and *PUB* is negative but not significant. This negative coefficient of interaction term indicates that *LOW_BDI* has no notable effect on the relationship between credit information sharing and stock price crash risk. The reason that the interaction term is insignificant is possible because there is not much variation in the value of the business extent of disclosure index in our sample (*BDI* on Panel B of Table 4-3) and most values cluster at the value of seven. Thus, in comparison to mandatory IFRS adoption, employing BDI as a proxy of the transparency of the information environment is not suitable.

4.4.1.3 The Impact of Bank Regulation on the Relationship between Credit Information Sharing and Stock Price Crash Risk

In general, bank regulators use bank regulations as an external mechanism to monitor banks so that they are more disciplined and do not engage in undesirable activities. If banks face strict regulatory environments, then they are more likely to behave prudently and have less ability to hide bad news. Thus, in this section, we test whether the relationship between credit information sharing and stock price crash risk varies with each of three aspects of bank regulations, consisting of capital stringency requirements, supervisory power, and private monitoring.

Firstly, our hypothesis H3-A says that the impact of credit information sharing on crash risk is expected to be more pronounced with less stringent capital requirements. Secondly, our hypothesis H3-B says that the impact of credit information sharing on crash risk is expected to be more pronounced with low supervisory power. Lastly, our hypothesis H3-C says that the impact of credit information sharing on crash risk is expected to be more pronounced with a low degree of private monitoring. Table 4-11 reports all the regression results.

In correspondence with the previous section, we use *PUB* to test our hypotheses. The column 1 and 2 of Table 4-11 present the regression results for Equation (4-10) regarding the impact of capital stringency requirements on the relationship between credit information sharing and crash risk. As shown in column 2, the coefficient of the interaction term between *LOW_CAPITAL_STR* and *PUB* is negative and significant. Consistent with our hypothesis H3-A, the negative coefficient of the interaction term suggests that the impact of information sharing through public credit registries on crash risk is more pronounced with less stringent capital requirements. If banks are not required to put a substantial amount of their equity at risk, they may not be cautious in lending and might take an excessive risk like concealing bad news for an extended period.

By assessing the marginal effect of capital stringency requirements on the relationship between credit information sharing and crash risk, we find that a one-percentage increase of *PUB* will lead to a 0.005 decrease in *NCSKEW* when the capital stringency requirements are high. However, when the capital stringency requirements are low, a one-percentage increase of *PUB* will lead to a 0.038 decrease in *NCSKEW*. In comparison to the countries with high capital stringency requirements, the impact of information sharing through public credit registries on crash risk is seven times more pronounced (or approximately 0.034 differences) in the countries with low capital stringency requirements. Thus, our result indicates that less stringent capital requirements may induce loan officers to behave riskily and accumulate bad news, such that forcing banks to share borrower information tends to be more helpful in reducing crash risk.

Column 3 and 4 of Table 4-11 present the regression results for Equation (4-11) with respect to the impact of the official supervisory power on the relationship between credit information sharing and crash risk. As shown in columns 4, the coefficient of the interaction term between *LOW_SUPER_POW* and *PUB* is negative and significant. Consistent with our hypothesis H3-B, the negative coefficient of the interaction term suggests that the impact of information sharing through public credit registries on crash risk is more pronounced with lower supervisory power. If bank supervisors do not have adequate powers to closely monitor banks, banks may engage in undesirable activities, notably complex banking activities.

We also evaluate the marginal impact of the supervisory power of the relationship between credit information sharing and crash risk. When the supervisory power is high, a one-percentage increase of *PUB* will lead to a 0.004 decrease in *NCSKEW*. However, when the supervisory power is low, a one-percentage increase of *PUB* will lead to a 0.056 decrease in *NCSKEW*. In comparison to the countries with high supervisory power, the impact of information sharing through public credit registries on crash risk is eleven times more pronounced (approximately 0.051 differences) in the countries with low supervisory power. Thus, our result indicates that, when banks are weakly regulated and monitored by their supervisors, they may behave opportunistically and hide bad news for an extended period, such that forcing banks to share borrower information becomes more useful in reducing crash risk.

Column 5 and 6 of Table 4-11 present the regression results for Equation (4-12) concerning the impact of private monitoring on the relationship between credit information sharing and crash risk. As shown in columns 6, the coefficient of the interaction term between *LOW_MONITOR* and *PUB* is negative and significant. Consistent with our hypothesis H3-C, the negative coefficient of the interaction term suggests that the impact of information sharing through public credit registries on crash risk is more pronounced with a lower degree of private monitoring.

High degree of the private monitoring means that banks are encouraged to disclosure more and accurate information to the public, so external investors have the ability and more incentives to overcome informational barriers and transaction costs. Therefore, in an environment with a low degree of private monitoring, banks are less transparent than those in an environment with high degree. In this regard, our result indicates that forcing banks to share borrower information tends to be more beneficial in an environment with a low degree of private monitoring.

By estimating the marginal effect of private monitoring on the relationship between credit information sharing and crash risk, we find that a one-percentage increase of *PUB* will lead to a 0.005 decrease in *NCSKEW* when the degree of private monitoring is high. However, when the degree of private monitoring is low, a one-percentage increase of *PUB* will lead to a 0.046 decrease in *NCSKEW*. In comparison to the countries with high degree of private monitoring, the impact of information sharing on crash risk is nine times more pronounced (approximately 0.041 differences) in the countries with a low degree of private monitoring. This marginal effect indicates that less emphasizing private monitoring tends to reduce the beneficial impact of credit information sharing on crash risk.

Overall, the results suggest that three aspects of bank regulations have significant and sizable impacts on the link between credit information sharing and crash risk. Less stringent capital requirements, low supervisory power and less emphasizing private monitoring contribute to weaker regulatory environments to the extent that credit information sharing has a more pronounced impact on crash risk. In other words, when the regulatory environments are weak, credit information sharing is more useful in reducing crash risk. Furthermore, among three aspects of bank regulations, we find that credit information sharing tends to be much more useful in reducing crash risk with less powerful bank supervisors than high capital stringency requirements and high emphasis on private monitoring.

4.4.2 Robustness Tests

In this section, we perform several robustness tests of our main results. First, we employ another alternative measure of crash risk called "Down-to-Up Volatility" (*DUVOL*). Second, to confirm our main results regarding the hypotheses H2, H3-A, H3-B, and H3-C, we split the sample into two samples based on proxies of the transparency of the information environment and median values of bank regulatory variables. and then estimates each subsample separately. Third, we augment each of Equation (4-8), (4-9), (4-10), (4-11), and (4-12) with additional control variables to control for factors that can potentially affect bank-specific stock price crash risk. Fourth, because the majority of banks in the sample are banks in the USA, so we try to exclude those banks to see whether our main results are still upheld. Last but not least, we address a possible endogeneity problem that may be associated with our previous regressions. Overall, our main results in the previous section are robust to these robustness tests. The following sections will discuss the robustness tests in detail.

4.4.2.1 Alternative measure of stock price crash risk

As to test for the robustness of the main results, we consider another depended variable as an alternative measure of crash risk. We consider the down-to-up volatility measure (*DUVOL*). It is the natural logarithm of the ratio of the standard deviation of the group with "down" weeks (the returns below the yearly mean) to the standard deviation of the group with "up" weeks (the returns above the yearly mean. The method of calculation is outlined in the Data and Methodology section.

We re-estimate each of Equation (4-8), (4-9), (4-10), (4-11) and (4-12) by using *DUVOL* as a dependent variable. Table 4-12 presents the regression results for Equation (4-8) testing our hypothesis H1. We can see that crash risk measured by *DUVOL* is negatively and significantly associated with *PUB* but not *DEPTH* and *PRIV*. By evaluating the marginal impact of *PUB* on *DUVOL*, a one-percentage increase of *PUB* will lead to a 0.002 decrease in *DUVOL*. The significantly negative coefficient of *PUB* support our hypothesis H1. The result is similar to the main result in the previous section suggesting that bank-specific stock price crash risk is likely to be lower in the countries with more coverage of credit information sharing among banks through public credit registries.

Table 4-13 shows the regression results for Equation (4-9) when we use *DUVOL* as a dependent variable. As shown on column 2 of Table 4-13, the coefficient of the interaction between *IFRS* and *PUB* is positive and significant (at the 10% level) meaning that the impact of *PUB* on crash risk, as measured by *DUVOL*, is lower with IFRS adoption. The significantly positive interaction term is like the main result and support our hypothesis H2 suggesting that the impact of credit information sharing on crash risk is lower with more transparent information environment as proxied by IFRS adoption. On the one hand, when the countries do not adopt IFRS, a one-percentage increase of *PUB* is associated with a 0.00335 decrease in *DUVOL*. On the other hand, when the countries adopt IFRS, a one-percentage increase of *PUB* is associated with a 0.00164 decrease in *DUVOL*. The impact of *PUB* on *DUVOL* is one-half time less pronounced with IFRS adoption. As shown on the column 4 of Table 4-13, the coefficient of the interaction between *LOW_BDI* and *PUB* is positive but not significant. Like the main result, the insignificant coefficient of the interaction term does not support our hypothesis H2 implying that the impact of credit information sharing on crash risk does not vary with different degree of business extent of disclosure index.

Next, Table 3-14 displays the regression results for Equation (4-10), (4-11) and (4-12) by using *DUVOL* as a dependent variable. The results are all in line with the main results. Regarding to the capital stringency index of Equation (4-10), the coefficient of the interaction between *LOW_CAPITAL_STR* and *PUB* on column 2 of Table 3-14 is significantly negative (at the 1% level) consistent with the hypothesis H3-A. It suggests that the impact of credit information sharing on crash risk is more pronounced when capital requirement is less stringent. Economically, on the one hand, when the capital stringency is high, a one-percentage increase of *PUB* is corresponding to a 0.00201 decrease in *DUVOL*. On the other hand, when the capital stringency is low, a one-percentage increase of *PUB* will lead to a 0.01012 decrease in *DUVOL*. That is 0.00811 additional decrease in *DUVOL* when the capital stringency is low.

Regarding the supervisory power index of Equation (4-11), the coefficient of the interaction between *LOW_SUPER_POW* and *PUB* on column 4 of Table 3-14 is significantly negative (at the 5% level) consistent with the hypothesis H3-B. It suggests that the impact of credit information sharing on crash risk is more pronounced when the supervisory power is low. Economically, on the one hand, when the supervisory power is high, a one-percentage increase of *PUB* is corresponding to a 0.00193 decrease in *DUVOL*. On the other hand, when the supervisory power is low, a one-percentage increase of *PUB* will lead to a 0.01457 decrease in *DUVOL*. That is 0.01264 additional decrease in *DUVOL* when the supervisory power is low.

Regarding a private monitoring of Equation (4-12), the coefficient of the interaction between *LOW_MONITOR* and *PUB* on column 6 of Table 3-14 is significantly negative (at the 1% level) consistent with the hypothesis H3-C. It suggests that the impact of credit information sharing on crash risk is more pronounced when the private monitoring is low. Economically, on the one hand, when the private monitoring is high, a one-percentage increase of *PUB* is corresponding to a 0.00201 decrease in *DUVOL*. On the other hand, when the supervisory power is low, a one-percentage increase of *PUB* will lead to a 0.01169 decrease in *DUVOL*. That is 0.968 additional decrease in *DUVOL* when the private monitoring is low.

4.4.2.2 Subsample Analysis

To further test the robustness of the main results, we split the sample based on our tested variables, which include proxies of the transparency of the information environment and bank regulatory variables. Regarding the proxy of the transparency of the information environment, we focus on only the adoption of IFRS because BDI is found insignificant in the main results. Regarding IFRS adoption, the sample is split into two groups which one group consists of countries that adopt IFRS and another group consists of countries that do not adopt IFRS. The information environment in countries that adopt IFRS is relatively more transparent than those that do not adopt IFRS. With regards to banking regulatory variables, the sample is split into two groups based on the median value of each banking regulatory variable. For each banking regulatory variable, one group consists of countries with values above the median value of the sample and another group consists of countries with values below the median value of the sample. We then estimate each subsample separately.

Table 4-15 reports the regression results of each subsample based on IFRS adoption. Clearly, the coefficient of *PUB* in the subsample without IFRS adoption is negative and significant (at 10% level) whereas the coefficient of *PUB* is not significant in the subsample with IFRS adoption. The significant coefficient of *PUB* in the subsample without IFRS adoption suggests that credit information sharing is important and associated with lower crash risk when the transparency of information environment is low. Economically, in the subsample without IFRS adoption, a one-percentage increase of *PUB* is associated with a 0.00782 decrease in *NCSKEW*. The insignificant coefficient of *PUB* in the subsample with IFRS adoption suggests that the impact of credit information sharing on crash risk is not only less pronounced but also not significant when the transparency of information environment is high.

Column 1 and 2 of Table 4-16 report the regression results of each subsample based on the median value of capital stringency index (*CAPITAL_STR*). Since the median value of *CAPITAL_STR* is 7, the first group contains countries with *CAPITAL_STR* above 7 whereas the second group contains countries with *CAPITAL_STR* below 7. Column 1 of Table 4-16 reports the regression result of the above-median group and shows that the coefficient of *PUB* is not significant. In contrast, column 2 of Table 4-16 reports the regression result of the below-median group and shows that the coefficient of *PUB* is negative and significant (at 1% level). Thus, the impact of credit information sharing on crash risk only have a significant impact in the subsample with low capital stringency. Economically, in the below-median group, a one-percentage increase of *PUB* is associated with a 0.00632 decrease in *NCSKEW*.

Column 3 and 4 of Table 4-16 report the regression results of each subsample based on the median value of supervisory power index (*SUPER_POW*). Since the median value of *SUPER_POW* is 10, the first group contains countries with *SUPER_POW* above 10 whereas the second group contains countries with *SUPER_POW* below 10. Column 3 of Table 4-16 reports the regression result of the above-median group and shows that the coefficient of *PUB* is not significant. In contrast, column 4 of Table 4-16 reports the regression result of the below-median group and shows that the coefficient of *PUB* is negative and significant (at 5% level). Thus, the impact of credit information sharing on crash risk only have a significant impact in the subsample with low supervisory power. Economically, in the below-median group, a one-percentage increase of *PUB* is associated with a 0.00527 decrease in *NCSKEW*.

Column 5 and 6 of Table 4-16 report the regression results of each subsample based on the median value of private monitoring index (*MONITOR*). Since the median value of *MONITOR* is 8, the first group contains countries with *MONITOR* above 8 whereas the second group contains countries with *MONITOR* below 8. On the one hand, column 5 of Table 4-16 reports the regression result of the above-median group and shows that the coefficient of *PUB* is negative and significant (at 5% level). On the other hand, column 6 of Table 4-16 reports the regression result of the below-median group and shows that the coefficient of *PUB* is negative and significant (at 1% level). By comparison with the coefficient of *PUB* in the above-median group, the coefficient of *PUB* in the below-median group is much more significant (at 1% versus at 5% level) and even have much more magnitude. Specifically, a one-percentage increase of *PUB* decreases *NCSKEW* by 0.00413 and 0.00759 for the above-median group and the below-median group, respectively. Thus, in comparison with the above-median group, the one-percentage increase of *PUB* in the below-median group leads to an additional decrease of *NCSKEW* by 0.00346.

4.4.2.3 Additional Controls

In addition, we add a series of macro institutional indexes in our model to test the robustness of the results. These variables are six components of the World Governance Indicators (Kaufmann *et al.* 2011), which capture different aspects of the institutional environment. The detailed definition of the indexes can be found in the data section. These governance indicators enter the regression individually (one at a time) because they are highly correlated with one another. We re-estimate each of Equation (4-8), (4-9), (4-10), (4-11) and (4-12) with additional control variables. The regression results are presented in Table 4-17 to Table 4-21. Overall, none of the governance indicators is significant, and in each column, the main results regarding the impact of credit information sharing on stock price crash risk are still upheld.

4.4.2.4 Non-USA Sample

Next, we exclude banks in the USA to see whether our main results are still robust. The regression results are presented in Table 4-22 for Equation (4-8) and Table 4-23 for the Equation (4-9) to (4-12). Overall, the results show that exclusion of banks in the USA does not change our main results. Our main results are still upheld. Specifically, on Table 4-22, we can only see that the coefficient of *PUB* in column 3 is significantly negative, except the coefficient of *DEPTH* and *PRIV*. Moreover, the coefficient of *PUB* is not only significant but also slightly more negative than the one in the main sample.

Economically, a one-percentage increase in *PUB* is associated with a 0.006 decrease in *NCSKEW*. In addition, when a country does not adopt IFRS, a one-percentage increase of *PUB* will decrease *NCSKEW* by 0.008. However, when a country adopts IFRS, a one-percentage increase of *PUB* will decrease *NCSKEW* by 0.005. That is 0.003 or approximately 37.5% less pronounced with IFRS adoption.

By evaluating the interaction between *PUB* and *LOW_CAPITAL_STR*, we find that a one-percentage increase in *PUB* is associated with a 0.006 decrease in *NCSKEW* when the capital stringency requirements are high (*LOW_CAPITAL_STR*=0). In contrast, when the capital stringency requirements are low (*LOW_CAPITAL_STR*=1), a one-percentage increase in *PUB* is now associated with a 0.035 decrease in *NCSKEW*. We can see that the impact of *PUB* on *NCSKEW* is more pronounced when the capital requirements are less stringent.

According to the interaction between *PUB* and *LOW_SUPER_POW*, we find that a one-percentage increase in *PUB* corresponds to a 0.006 decrease in *NCSKEW* when the supervisory power is high (*LOW_SUPER_POW* = 0). However, when the supervisory power is low (*LOW_SUPER_POW* = 1), a one-percentage increase in *PUB* now corresponds to a 0.051 decrease in *NCSKEW*. We can see that the impact of *PUB* on *NCSKEW* is more pronounced when the supervisory power is low.

According to the interaction between *PUB* and *LOW_MONITOR*, the results show that a one-percentage increase in *PUB* is associated with a 0.006 decrease in *NCSKEW* when the degree of private monitoring is high (*LOW_MONITOR* = 0). In contrast, when the degree of private monitoring is low (*LOW_MONITOR* = 1), a one-percentage increase in *PUB* is now associated with a 0.035 decrease in *NCSKEW*. We can see that the impact of *PUB* on *NCSKEW* is more pronounced when the degree of private monitoring is low.

4.4.2.5 Instrumental Variable Approach

To avoid the problem of endogeneity, we rely on the instrumental variable approach[34]. Similar to Chapter 2 and Chapter 3, we choose instruments for *DEPTH* based on the literature on law and finance (Easterly & Levine 1997; LaPorta *et al.* 1998; La Porta *et al.* 1999; Beck *et al.* 2003; Acemoglu & Johnson 2005). These instruments are legal origins, ethnic fractionalization, and latitude[35]. Since these instrumental variables are time-invariant, we perform a two-stage least square (2SLS) with pooled OLS estimations rather than fixed effects estimations.

The Durbin-Wu-Hausman test of endogeneity shows that the null hypothesis cannot be rejected at 1% (p-value=0.1930), so *DEPTH* can be treated as exogenous. Nonetheless, we perform robustness tests for Equation (4-8) to (4-12) by employing an instrumental variable approach. The test of instruments and the IV regression results are presented in Table 4-24 to Table 4-28. In all regression, the F-test of the excluded instruments in the corresponding first-stage regression shows that the null hypothesis is rejected at the 1%. Thus, our instruments are relevant. The Hansen J-test of over-identifying restrictions cannot be rejected suggesting that the instruments are valid instruments, uncorrelated with the error term and correctly excluded from the estimated equation.

Next, we continue to analyze the IV regression results of each table. The results are presented in Table 4-24 to Table 4-28. First, we analyze the IV regression results for Equation (4-8). On Table 4-24, the first column reports the second stage regression, while

[34] The reverse causality between credit information sharing and crash risk is less problematic because we investigate the impact of credit information sharing agencies on crash risk of individual bank firms.
[35] Refer to Appendix G for the rationales behind selecting instruments

the second column reports the first stage regression. The main result is still robust and consistent with our first hypothesis H1. The coefficient of *DEPTH* remains positive and significant. The result with IV approach confirms our main finding that bank stock price crash risk decreases with credit information sharing. Moreover, the IV coefficient is much larger than the coefficient of the fixed effect regression, indicating the presence of potential measurement error, which inflates the IV coefficient. Nonetheless, our conclusion does not depend on the instrumentation approach because *DEPTH* is not endogenous and poses no concern of endogeneity.

For the regression results of Equation (4-9) to (4-12), we split the sample into two subsamples based on the adoption of IFRS and the banking competition measure. Table 4-25 presents the IV regressions of two subsamples that are split based on *IFRS* as a proxy of information environment transparency. The results are robust and consistent with our second hypothesis H2. The coefficient of *DEPTH* is only significant in the subsample without the mandatory IFRS adoption suggesting that the impact of credit information sharing on bank risk is more pronounced when the information environment is less transparent.

Table 4-26, Table 4-27 and Table 4-28 present the IV regressions of two subsamples which are split based on the median value of capital stringency index, supervisory power index and private monitoring index, respectively. Consistent with our hypothesis H3-A, Table 4-26 shows that the coefficient of *PUB* is merely significantly negative in the subsample with low capital stringency indexes. Consistent with our hypothesis H3-B, Table 4-27 reveals that the coefficient of *PUB* is merely significantly negative in the subsample with low supervisory power indexes. Consistent with our hypothesis H3-C, Table 4-28 shows that the coefficient of *PUB* is merely significantly negative in the subsample with low private monitoring indexes. The IV regression results in Table 4-26, Table 4-27 and Table 4-28 suggest that the impact of credit information sharing on crash risk is more pronounced in the subsample with low capital stringency index, the subsample with low supervisory power indexes and the subsample with low private monitoring indexes, respectively.

4.4.3 Additional Tests

4.4.3.1 Existence of Deposit Insurance Regime

In this section, we attempt to examine the impact of another aspect of bank regulation on the relationship between credit information sharing and stock price crash risk. We consider the existence of deposit insurance. Specifically, we include a deposit insurance dummy (*DEPOSIT_INS*), which takes a value of one if a country has explicit deposit insurance and a value of zero otherwise. As pointed out by Barth *et al.* (2006), deposit insurance intensifies the moral hazard problem in banking because depositors no longer face the risk of losing their savings, which diminishes their incentives and efforts at monitoring bank activities (Houston *et al.* 2010).

The deposit insurance scheme is a kind of depositor protection mechanism which internalizes risk of banking management (Keeley 1990). Theoretically, deposit insurance schemes are designed to prevent bank runs (when depositors attempt to withdraw their funds all at once) by supporting failing banks with necessary resources (Keeley 1990; Matutes & Vives 1996; Diamond & Dybvig 2000; Demirgüç-Kunt *et al.* 2008). There is also the potential for contagious bank runs on other healthy banks (Allen & Gale 2000). Therefore, many countries enact deposit insurance schemes to improve banking sector stability and reduce the probability of systemic crises (Demirgüç-Kunt & Detragiache 2002). However, since deposit insurance could protect the interest of depositors by guaranteeing deposits, depositors then have lower incentive to monitor and supervise bank's risk-taking behavior (Demirgüç-Kunt & Huizinga 2004; Ioannidou & Penas 2010), which will exacerbate the bank moral hazard problem as well as the likelihood of banking crisis (Demirgüç-Kunt & Detragiache 2002; Barth *et al.* 2004). Thus, deposit insurance can encourage excessive risk-taking by banks and banks are likely to hoard bad news and become less disciplined which consequently could lead to crash risk. We expect that the impact of credit information sharing on the crash is expected to be more pronounced when there is the existence of deposit insurance.

The regression results are reported in the first two columns of Table 4-29. The interaction term between *PUB* and *DEPOSIT_INS* is negative and significant (at 1% level), suggesting that the impact of credit information sharing on crash risk is more pronounced when a deposit insurance regime exists. This shows that, in comparison to no deposit insurance regime, the existence of deposit insurance regime causes banks to become less disciplined and engage in greater risk-taking; therefore, the role of credit information sharing on crash risk is more pronounced.

4.4.3.2 Activity Restriction

As documented in Barth *et al.* (2006), proponents of restricting bank activities argue that broad financial activities may intensify moral hazard problems and provide banks an incentive to engage in risk-taking behaviors (Boyd *et al.* 1998). With their ability to engage in broad financial activities, banks may become extremely large and very complex. When they are very large and complex, they are hard to monitor and also too large to discipline (Laeven & Levine 2007). Thus, restrictions on banks' activities help prevent moral hazard problems and the formation of extremely large and complex organization that are hard to monitor and discipline. By compelling banks to do what they do best and to maintain simple balance sheets, activity restrictions should lead to improved efficiency. Therefore, when banks are not restricted to engage in broader financial activities, then they expand themselves into securities activities, insurance activities, real estate activities or even nonfinancial activities and banks can extremely large and complex and less disciplined. As a result, banks are likely to engage in greater risk-taking such as hide bad news activities which may consequently lead to crash risk.

Opponents of restricting banks' activities argue that such restrictions prevent banks from achieving economies of scope and scale in gathering and processing information about firms, building reputational capital and facilitating various types of services to customers (Barth *et al.* 2000; Laeven & Levine 2007). Furthermore, restricting banks' activities could also hinder banks from diversifying their income sources and reduce their franchise value, which might cause them to engage in risk-taking behavior (Claessens & Klingebiel 2001; Barth *et al.* 2004). In addition, according to the private interest view, such restrictions only give discretion to the regulators and thereby increase their bargaining power, which is not necessarily good for the sector (Djankov *et al.* 2002). This view suggests that restrictions on banks' activities hinders their efficiency and performance.

Thus, if the underlying rationales behind restricting bank activity is true and banks can become extremely complex and hard to monitor when the rules on activity restriction is not very stringent, then we would expect to see the impact of credit information sharing on crash risk to be more pronounced (when the level of activity restriction low). However, the regression results in the last columns of Table 4-29 report that the interaction term between *PUB* and *LOW_ACTIVITY_RES* is positive but not significant, meaning that the impact of credit information sharing on crash risk does not vary with the level of activity restriction on banks. The insignificance of the interaction suggests that, although fewer restrictions on broad financial activities may cause banks to complex and hard to monitor/discipline, fewer restrictions also prevent banks from engaging in risk-taking behaviors as they can achieve economies of scope and scale and diversify their income sources. One force of fewer restriction tends to make banks less disciplined and engage in greater risk-taking, but another force of low restriction suggests that banks can diversify and behave prudently. These two forces may offset each other making the result, not in line with our prediction that the impact of credit information sharing on crash risk is more pronounced with low activity restriction.

4.5 Conclusion

This chapter investigates the role of credit information sharing in reducing future stock price crash risk. Using a sample of 1,402 banks in 55 countries during 2005-2013, we find evidence that credit information sharing has a negative impact on future stock price crash risk of bank-specific returns. Our results hold only for information sharing through public credit registries, whereas information sharing through private credit bureaus has no significant impact on crash risk. Compared to public credit registries, private credit bureaus are not compulsory and less regulated, such that it may involve self-selection bias. Opaque banks may not join the bureaus in the first place to share borrower information. Overall, the results are robust to an alternative measure of crash risk, adding more control variables, a subsample analysis, and an instrumental variable approach.

Our findings are consistent with the notion that forcing banks to share borrower information sharing may discourage loan officers to hide bad news for an extended period and subsequently lead to a reduction in stock price crash risk. Specifically, credit information sharing can help to monitor loan officers and to prevent corruption in lending. In addition, sharing borrower information from one bank will be beneficial to another bank's manager validating internal risk ratings and preventing loan officers from biasing their borrower reports. Moreover, credit information sharing may improve comparability that discourages hiding bad news. Therefore, with more credit information sharing, loan officers are less likely to conceal negative information about their borrowers for an extended period. Consequently, negative information is less likely to be accumulated and the probability of an asset price crash decreases.

Furthermore, we proxy the transparency level of information environment by the mandatory adoption of IFRS and show that it attenuates the impact of credit information sharing on crash risk. The finding suggests that the negative relationship between credit information sharing and crash risk is less pronounced when the information environment is more transparent. In an environment with a higher level of information transparency, loan officers have less ability to conceal negative information about borrowers as more information is accessible to both investors and loan managers. Thus, in the more transparent information environment, information sharing may be less useful in lowering crash risk.

Regarding bank regulations, we find evidence that the negative relationship between credit information sharing and crash risk is more pronounced with less stringent capital requirements, low supervisory power and low degree of private monitoring. Our results indicate that, when the banking regulatory environments are weak, it is more useful to reduce crash risk by forcing banks to share borrower information. This finding suggests that, amid the weakness of the regulatory environments, information sharing may discourage banks to undergo undesirable activities like concealing bad news, such that it leads to lower stock price crash risk. Of all three aspects of bank regulations, the results also reveal that credit information sharing is much more useful in reducing crash risk with less powerful bank supervisors than less stringent capital requirements and less emphasis on private monitoring.

Figure 4-1: Diagram for Research Question 1

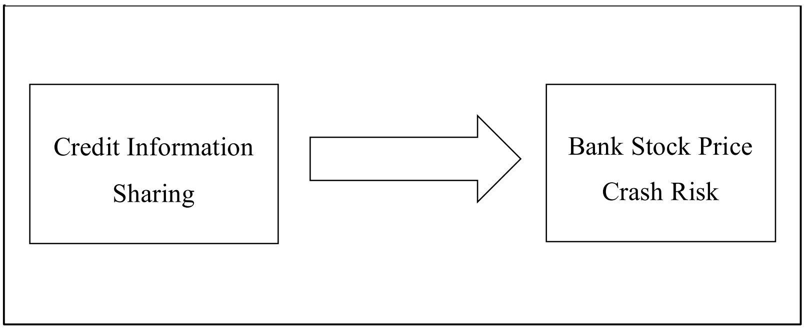

Figure 4-2: Diagram for Research Question 2

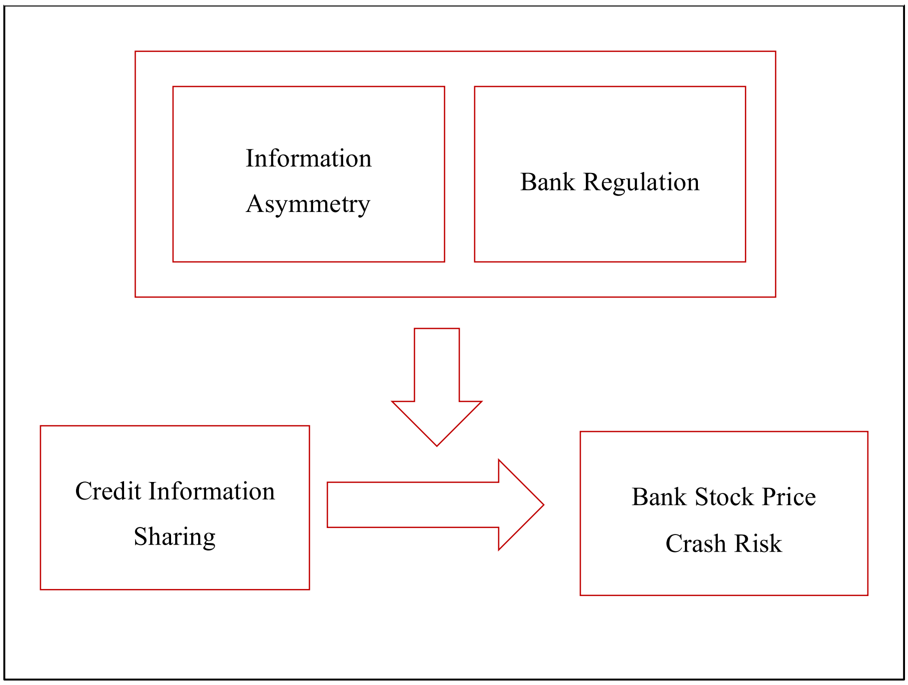

Table 4-1: Summary of Variables, Symbols and Sources

Variable			Description	Source
Dependent Variables	NCSKEW	Negative Conditional Skewness of Returns	It is a negative conditional skewness of firm-specific weekly returns over fiscal year. Specifically, $NCSKEW$ for a give firm in a fiscal year is calculated by taking the negative of the third moment of firm-specific weekly returns for each sample year and dividing (normalizing) it by the standard deviation of firm-specific weekly returns raised to the third power (Chen *et al.* 2001; Kim *et al.* 2011b). Specifically, for each firm i in a year, $NCSKEW$ is computed as: $NCSKEW_{i,t} = -\left[n(n-1)^{3/2}\sum W_{i,t}^{3}\right] \Big/ \left[(n-1)(n-2)\left(\sum W_{i,t}^{2}\right)^{3/2}\right]$ *Higher NCSKEW indicates higher stock price crash risk*	Datastream; Bankscope
	DUVOL	Down-to-Up Volatility of Returns	It is the down-to-up volatility measure of the crash likelihood ($DUVOL$). For each firm i over a fiscal year, firm-specific weekly returns are classified into two groups, “down” and “up”. The first group with “Down” weeks consists of the returns that are below the yearly mean and the second group with “Up” weeks consists of the returns that are above the yearly mean. Then standard deviation of firm-specific weekly returns is estimated separately for each of these two groups; and the volatility of down-to-up is calculated by taking the natural logarithm of the ratio of the standard deviation of the group with “down” weeks to the standard deviation of the group with “up” weeks as shown below: $DUVOL_{i,t} = log\left[(n_u - 1)\sum_{DOWN} W_{i_d,t}^{2} \Big/ (n_d - 1)\sum_{UP} W_{i_u,t}^{2}\right]$ *Higher DUVOL indicates higher stock price crash risk*	Datastream; Bankscope
Explanatory Variables	DEPTH	Depth of Credit Information Sharing index	An index that measures the scope and contents of credit information that being shared. It ranges from zero to six. The value of zero indicates that there is no public credit registry or private credit bureau operating in a country. The value of one is added to the index with each of the following characteristics: • Both positive and negative information are distributed. • Data on households and firms are distributed. • Data from retailers, trade creditors, and/or utility companies as well as financial institutions are distributed. • More than 2 years of data are available. • Data are collected and distributed on loans with value below 1% of income per capita.	World Bank’s Doing Business database; Djankov *et al.* (2007)

			• Laws give right to borrowers to inspect their own data. *Higher DEPTH indicates more credit information*	
	PRIV	Private Credit Bureau Coverage (%)	The number of individuals and firms listed by a private credit bureau with information on repayment history, unpaid debts, or credit outstanding from the past five years scaled by the adult population *Higher PRIV indicates more credit information (through private credit bureaus)*	World Bank's Doing Business database; Djankov *et al.* (2007)
	PUB	Public Credit Registry Coverage (%)	The number of individuals and firms listed in a public credit registry with information on repayment history, unpaid debts, or credit outstanding from the past five years scaled by adult population *Higher PUB indicates more credit information (through public credit registries)*	World Bank's Doing Business database; Djankov *et al.* (2007)
	IFRS	International Financial Reporting Standard (IFRS) adoption	A dummy variable whose value is equal to 1 for a country (and year) that adopts IFRS and 0 otherwise. *A value of one (zero) indicates more (less) transparent information environment*	IFRS foundation website, Deloitte and Simon Fraser University in Canada
	LOW_BDI	Low Business Extent of Disclosure Index	This dummy variable is derived from BDI (business extent of disclosure index). BDI measures the extent to which investors are protected through disclosure of ownership and financial information (World Bank's Doing Business 2016). It ranges from 0 to 10 with higher value indicating more disclosure of ownership and financial information to investors. We assign a dummy variable equal to 1 for a country with a value of BDI lower than the sample 50th percentile and zero for those above the sample 50th percentile. *A value of one (zero) indicates less (more) transparent information environment*	World Bank's Doing Business
	LOW_CAPITAL_STR	Low Capital Stringency Index	This dummy variable is derived from CAPITAL_STR (capital stringency index). CAPITAL_STR is an index measuring the extent of both initial and overall capital stringency. This index is constructed from following questions: 1. Whether the minimum capital-asset ratio requirement is in line with the Basel Committee on Banking Supervision guidelines 2. Does the minimum ratio varies as a function of an individual bank's credit risk?	World Bank's Bank Regulation and Supervision Survey Database

			3. Does the minimum ratio varies as a function of an individual bank's market risk? 4. Before minimum capital adequacy is determined, which of the following are deducted from the book value of capital: a. Market value of loan losses not realized in accounting books? b. Unrealized losses in securities portfolios? c. Unrealized foreign exchange losses? 5. What fraction of revaluation gains is allowed as part of capital? (1 if the fraction is less than 0.75 and 0 otherwise) 6. Are the sources of funds to be used as capital verified by the regulatory/supervisory authorities? 7. Can the initial disbursement or subsequent injections of capital be done with assets other than cash or government securities? 8. Can initial capital contributions by prospective shareholders be in the form of borrowed funds? The index ranges from 0 to 10. We assign a dummy variable equal to 1 for a country with a value of CAPITAL_STR lower than the sample 50th percentile and zero for those above the sample 50th percentile. *A value of one (zero) indicates less (more) capital stringent requirement*	
	LOW_SUPER_POW	Low Official Supervisory Power index	This dummy variable is derived from SUPER_POW (supervisory power index). SUPER_POW is an index measuring the power of officers in supervising and monitoring banks in each country. This index is constructed from the following questions: 1. Does the supervisory agency have the right to meet with external auditors to discuss their report without the approval of the bank? 2. Are auditors required by law to communicate directly to the supervisory agency any presumed involvement of bank directors or senior managers in illicit activities, fraud, or insider abuse? 3. Can supervisors take legal action against external auditors for negligence? 4. Can the supervisory authority force a bank to change its internal organizational structure? 5. Are off-balance sheet items disclosed to supervisors? 6. Can the supervisory agency order the bank's directors or management to constitute provisions to cover actual or potential losses?	World Bank's Bank Regulation and Supervision Survey Database

			7. Can the supervisory agency suspend the directors' decision to distribute: a. Dividends? b. Bonuses? c. Management fees? 8. Can the supervisory agency legally declare – such that this declaration supersedes the rights of bank shareholders – that a bank is insolvent? 9. Does the Banking Law give authority to the supervisory agency to intervene, that is, suspend some or all ownership rights of a problem bank? 10. Regarding bank restructuring and reorganization, can the supervisory agency or any other government agency do the following: a. Supersede shareholder rights? b. Remove and replace management? c. Remove and replace directors? The index ranges from 0 to 14. We assign a dummy variable equal to 1 for a country with a value of SUPER_POW lower than the sample 50th percentile and zero for those above the sample 50th percentile. *A value of one (zero) indicates less (more) supervisory power*	
	LOW_MONITOR	Low Private Monitoring Index	This dummy variable is derived from MONITOR (private monitoring index). MONITOR is an index measuring the extent of regulation and supervisory policies in shaping the incentives and ability of private investors to monitor and exert effective governance over banks in each country. This index is constructed from the following questions: 1. Whether bank officials are legally liable if the information disclosure is erroneous or misleading? 2. Whether banks disclosure information such as: a. Consolidated accounts covering all bank and any non-bank financial subsidiaries? b. Off-balance sheet items? c. Accrued, though unpaid interest/principal of non-performing loan? d. Risk management procedures to the public? 3. Whether banks must be audited by certified international auditors? 4. Whether the largest ten banks are rated by international rating agencies? 5. Whether the largest ten banks are rated by domestic rating agencies? 6. Whether subordinated debt is allowable as part of capital?	World Bank's Bank Regulation and Supervision Survey Database

			7. Whether there is no explicit deposit insurance system and no insurance was paid the last time a bank failed? The index ranges from 0 to 10. We assign a dummy variable equal to 1 for a country with a value of MONITOR lower than the sample 50th percentile and zero for those above the sample 50th percentile. *A value of one (zero) indicates less (more) private monitoring index*	
	DEPOSIT_INS	Deposit Insurance	A dummy variable indicating if the country had or not explicit deposit insurance system and zero otherwise. *A value of one (zero) indicates the existence (non-existence) of deposit insurance regime*	Demirgüç-Kunt *et al.* (2008)
	LOW_ACTIVITY_RES	Low Activity Restriction	This dummy variable is derived from ACTIVITY_RES (activity restriction index). ACTIVITY_RES is an index measuring the overall restrictions on banking activities, which include securities activities, insurance activities, real estate activities and activities in nonfinancial firms. 1. What are the conditions under which banks can engage in securities activities? a. Unrestricted = 1: A full range of these activities can be conducted in directly in banks. b. Permitted = 2: A full range of these activities are offered but all or some of these activities must be conducted in subsidiaries or in another part of a common holding company or parent. c. Restricted = 3: Less than the full range of activities can be conducted in banks, or subsidiaries, or in another part of a common holding company or parent. d. Prohibited = 4: None of these activities can be done in either banks or subsidiaries, or in another part of a common holding company or parent. 2. What are the conditions under which banks can engage in insurance activities? a. Unrestricted = 1: A full range of these activities can be conducted in directly in banks. b. Permitted = 2: A full range of these activities are offered but all or some of these activities must be conducted in subsidiaries or in	World Bank's Bank Regulation and Supervision Survey Database

			another part of a common holding company or parent. c. Restricted = 3: Less than the full range of activities can be conducted in banks, or subsidiaries, or in another part of a common holding company or parent. d. Prohibited = 4: None of these activities can be done in either banks or subsidiaries, or in another part of a common holding company or parent. 3. What are the conditions under which banks can engage in real estate activities? a. Unrestricted = 1: A full range of these activities can be conducted in directly in banks. b. Permitted = 2: A full range of these activities are offered but all or some of these activities must be conducted in subsidiaries or in another part of a common holding company or parent. c. Restricted = 3: Less than the full range of activities can be conducted in banks, or subsidiaries, or in another part of a common holding company or parent. d. Prohibited = 4: None of these activities can be done in either banks or subsidiaries, or in another part of a common holding company or parent. 4. Can banks own voting shares in nonfinancial firms? a. Unrestricted = 1: A bank may own 100% of the equity in any non-financial firm. b. Permitted = 2: A bank may own 100% of the equity in a non-financial firm but ownership is limited based upon a bank's equity capital. c. Restricted = 3: A bank can only acquire less than 100% of the equity in a non-financial firm. d. Prohibited = 4: A bank may not have any equity investment in a non-financial firm whatsoever. The index ranges from 0 to 16. We assign a dummy variable equal to 1 for a country with a value of ACTIVITY_RES lower than the sample 50^{th} percentile and zero for those above the sample 50^{th} percentile. *A value of one (zero) indicates less (more) activity restrictiveness.*	

Bank-Specific Controls	DTURN	Detrended Stock Turnover	The detrended average monthly stock turnover	Datastream
	SIGMA	Standard Deviation of bank-specific weekly return	The standard deviation of firm-specific weekly return over the year	Datastream
	MEAN	Mean of bank-specific weekly return	The average arithmetic mean of firm-specific weekly return over the year	Datastream
	MV	Market Value of Equity	The market value of equity	Datastream
	MTBV	Market-to-Book Value Ratio	The natural logarithm of the market value of equity divided by the value of equity	Datastream
	LEV	Leverage Ratio	A leverage ratio calculated as total liabilities to total assets	Datastream
	ROA	Return on Assets	A return on assets calculated as income before extraordinary items divided by total assets	Datastream
	CAR_TIER1	Tier 1 Capital Ratio	A tier1 capital adequacy ratio	Datastream
	DEPOSIT	Total Deposit to Total Asset Ratio	A ratio of total deposits to total assets	Datastream
	C_SCORE	Conditional Accounting Conservatism Score	Accounting conservatism refers to the tendency of accountants to require a higher degree of verification to recognize good news as gains than to recognize bad news as losses (Basu 1997; Kim & Zhang 2015). Conditional conservatism measures the incremental timeliness for recognizing bad news over good news. Following Khan and Watts (2009), we calculate C_SCORE to measure the conditional accounting conservatism for each bank-year. First, we estimate the equation below using five-year rolling panel regression for each country. $X_{jt} = \beta_{1t} + \beta_{2t}D_{jt} + R_{jt}(\mu_{1t} + \mu_{2t}MKV_{jt} + \mu_{3t}MB_{jt} + \mu_{4t}LEV_{jt}) + D_{jt}R_{jt}(\lambda_{1t} + \lambda_{2t}MKV_{jt} + \lambda_{3t}MB_{jt} + \lambda_{4t}LEV_{jt}) + (\delta_{1t}MKV_{jt} + \delta_{2t}MB_{jt} + \delta_{3t}LEV_{jt} + \delta_{4t}D_{jt}MKV_{jt} + \delta_{5t}D_{jt}MB_{jt} + \delta_{6t}D_{jt}LEV_{jt}) + \varepsilon_{jt}$ Second, we obtain λ_{1t} to λ_{4t} from the estimation above and plug them into the following equation to obtain C_SCORE: $C\_SCORE = \beta_{4j} = \lambda_1 + \lambda_2 MKV_j + \lambda_3 MB_j + \lambda_4 LEV_j$	Datastream and own calculation
Country-Specific Controls	GDPG	A growth rate of gross domestic products (GDP)	This variable is a growth rate of GDP. It captures macroeconomic developments and a proxy for fluctuation in economic activities.	World Development Indicators (WDI)
	MKTCAP	Stock Market Capitalization	The stock market capitalization scaled by GDP	World Development Indicators (WDI)
	GDPPC	Gross Domestic Product (GDP) Per Capital	The natural logarithm of GDP per capital	World Development

				Indicators (WDI)
	CORRUPTION	Control of Corruption index	This index captures perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests.	World Bank's *Worldwide Governance Indicators* (WGI)
	GOV_EFF	Government Effectiveness index	This index captures perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies.	World Bank's *Worldwide Governance Indicators* (WGI)
	POLITIC	Political Stability index	This index measures perceptions of the likelihood of political instability and/or politically-motivated violence, including terrorism.	World Bank's *Worldwide Governance Indicators* (WGI)
	REG_QUA	Regulatory Quality index	This index captures perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development.	World Bank's *Worldwide Governance Indicators* (WGI)
	RULE_LAW	Rule of Law index	This index captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence.	World Bank's *Worldwide Governance Indicators* (WGI)
	VOICE_ACC	Voice and Accountability index	This index captures perceptions of the extent to which a country's citizens can participate in selecting their government, as well as freedom of expression, freedom of association, and a free media.	World Bank's *Worldwide Governance Indicators* (WGI)
Instrumental Variables	LEGALORIGIN	Legal Origin	A dummy variable whose value is equal to one if a country has English legal origin and otherwise zero.	Djankov *et al.* (2007)
	ETHNIC_FRAC	Ethnic fractionalization	This variable captures the ethnic diversity in a country. It measures probability that two randomly selected people from a given country will not belong to the same ethnolinguistic group.	Easterly (2001)
	LATITUDE	Latitude	This variable measures the geographical latitude of a country. It is calculated as an absolute value of the latitude of the country scaled to take a value between zero and one	La Porta *et al.* (1999); Central Intelligence Agency (CIA)

Table 4-2: Descriptive Statistics

		Variable	N	Mean	Stdev.	Min	Max	P25	P50 (Median)	P75
Dependent Variables		***NCSKEW***	7562	-0.069	1.150	-6.920	6.980	-0.637	-0.038	0.552
		DUVOL	7562	-0.086	0.434	-3.590	3.020	-0.314	-0.078	0.151
Explantory Variables	**CIS**	***DEPTH***	7562	5.460	0.988	0.000	6.000	5.000	5.000	6.000
		PRIV	7562	0.771	0.370	0.000	1.000	0.630	1.000	1.000
		PUB	7562	0.115	0.106	0.000	1.000	0.000	0.061	0.277
	ASYM	***IFRS***	7562	0.888	0.315	0.000	1.000	1.000	1.000	1.000
		LOW_BDI	7562	0.106	0.308	0.000	1.000	0.000	0.000	0.000
	REG	***LOW_CAPITAL_STR***	7077	0.287	0.452	0.000	1.000	0.000	0.000	1.000
		LOW_SUPER_POW	7077	0.294	0.456	0.000	1.000	0.000	0.000	1.000
		LOW_MONITOR	7077	0.409	0.492	0.000	1.000	0.000	0.000	1.000
		DEPOSIT_INS	7077	0.947	0.223	0.000	1.000	1.000	1.000	1.000
		LOW_ACTIVITY_RES	7077	0.612	0.487	0.000	1.000	0.000	1.000	1.000
Bank-Specific Controls		***DTURN***	7562	-0.002	0.067	-0.942	0.794	-0.007	0.000	0.006
		SIGMA	7562	0.044	0.028	0.001	0.259	0.026	0.035	0.052
		MEAN	7562	-0.002	0.008	-0.137	0.029	-0.005	-0.001	0.002
		MV	7562	5.790	2.250	-2.410	12.500	4.120	5.550	7.240
		MTBY	7562	0.028	0.262	-0.143	13.600	0.010	0.014	0.020
		LEV	7562	0.909	0.043	0.330	1.090	0.892	0.914	0.934
		ROA	7562	0.005	0.015	-0.442	0.117	0.002	0.007	0.010
		DEPOSIT	7562	0.720	0.160	0.000	0.982	0.654	0.762	0.830
		CAR_TIER1	7562	0.124	0.056	-0.117	1.250	0.095	0.115	0.140
		C_SCORE	7562	1.760	1.660	-7.640	5.040	0.858	2.040	3.100
Country-Specific Controls		***GDPG***	7562	0.020	0.031	-0.148	0.180	0.008	0.023	0.034
		MKTCAP	7562	0.988	0.380	0.076	3.380	0.727	1.050	1.300
		GDPPC	7562	10.400	1.000	6.590	11.600	10.600	10.800	10.800
		CORRUPTION	7562	1.120	0.739	-1.200	2.550	1.260	1.310	1.380
		GOV_EFF	7562	1.310	0.616	-1.000	2.430	1.460	1.510	1.600
		POLITIC	7562	0.382	0.644	-2.810	1.510	0.374	0.488	0.635
		REG_QUA	7562	1.190	0.584	-0.728	1.970	1.120	1.400	1.540
		RULE_LAW	7562	1.280	0.667	-1.180	2.000	1.320	1.580	1.610
		VOICE_ACC	7562	0.903	0.622	-1.680	1.760	1.070	1.090	1.120
Instrumental Variables		***LEGALORIGIN***	7440	0.699	0.459	0.000	1.000	0.000	1.000	1.000
		ETHNIC_FRAC	7236	0.420	0.224	0.000	0.890	0.320	0.500	0.500
		LATITUDE	7539	0.686	0.078	0.314	0.835	0.691	0.691	0.691

The table presents summary statistic of variables. *NCSKEW* is a negative conditional skewness of returns and *DUVOL* is a down-to-up volatility of returns. *CIS* represents credit information sharing measures; *DEPTH* is depth of credit information sharing index; *PRIV* is private credit bureau coverage (% of adult population); *PUB* is public credit registry coverage (% of adult population); *ASYM* represents information environment proxies; *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *LOW_BDI* is a dummy variable whose value is equal to one if a country has low business extent of disclosure index and zero otherwise: *REG* represents banking regulatory variables; *LOW_CAPITAL_STR* is a dummy variable whose value is equal to one if a country has low capital stringency index and zero otherwise; *LOW_SUPER_POW* is a dummy variable whose value is equal to one if a country has low supervisory power index and zero otherwise; *LOW_MONITOR* is a dummy variable whose value is equal to one if a country has low private monitoring index and zero otherwise; *DEPOSIT_INS* is a dummy variable whose value is equal to one when there exist deposit insurance regime in the country; *LOW_ACTIVITY_RES* is a dummy variable whose value is equal to one if a country has low activity restriction index and zero otherwise; *DTURN* the detrended average monthly stock turnover; *SIGMA* is the standard deviation of firm-specific weekly return over the year; *MEAN* is the average arithmetic mean of firm-specific weekly return over the year; *MV* is the market value of equity; *MTBV* is the natural logarithm of the market value of equity divided by the value of equity; *LEV* is the leverage ratio calculated as total liability to total assets; *ROA* is a return on assets calculated as income before extraordinary items divided by total assets; *CAR_TIER1* is a tier1 capital adequacy ratio; *DEPOSIT* is a ratio of total deposits to total assets; *C_SCORE* is a measure of accounting conservatism; *GDPG* is real GDP growth; *MKTCAP* is the stock market capitalization scaled by GDP; *GDPPC* is the natural logarithm of GDP per capital; *CORRUPTION* is a control of corruption index; *GOV_EFF* is a government effectiveness index; *POLITIC* is a political stability index; *REG_QUA* is a regulatory quality index; *RULE_LAW* is a rule of law index; *VOICE_ACC* is a voice and accountability index; *LEGALORIGIN* is a dummy variable whose value is equal to one if a country has English legal origin; *ETHNIC_FRAC* is an ethnic fractionalization; *LATITUDE* is a country's latitude scaled to take a value between zero and one. Further detail of all variables are presented in Table 4-1 in this chapter. Obs is observation. Stdev is for standard deviation. Min is minimum. Max is maximum. P25 is 25th percentile of the sample. P50 is 50th percentile (or median) of the sample. P75 is 75th percentile of the sample.

Table 4-3: Descriptive Statistics - Grouped by Country

Panel A: Descriptive statistics of our main variables grouped by countries

Variable	Obs.	Mean	Stdev.	Min	Max	P25	P50 (Median)	P75
NCSKEW	55	-0.098	0.292	-0.586	0.909	-0.331	-0.091	0.084
DUVOL	55	-0.100	0.153	-0.381	0.467	-0.215	-0.090	-0.036
DEPTH	55	4.440	1.400	0.000	6.000	4.000	4.870	5.000
PRIV	55	0.410	0.365	0.000	1.000	0.075	0.315	0.790
PUB	55	0.114	0.215	0.000	1.000	0.000	0.061	0.141
IFRS	55	0.830	0.343	0.000	1.000	1.000	1.000	1.000
LOW_BDI	55	0.474	0.493	0.000	1.000	0.000	0.000	1.000
LOW_CAPITAL_STR	55	0.665	0.403	0.000	1.000	0.333	1.000	1.000
LOW_SUPER_POW	55	0.679	0.419	0.000	1.000	0.167	1.000	1.000
LOW_MONITOR	55	0.284	0.312	0.000	1.000	0.000	0.192	0.417

Panel B: Descriptive statistics for variables used to construct each of LOW_BDI, LOW_CAPITAL_STR, LOW_SUPER_POW and LO_MONITOR

Variable	Obs.	Mean	Stdev.	Min	Max	P25	P50 (Median)	P75
Bank-year								
BDI	7562	6.920	1.430	0.000	10.000	7.000	7.000	7.000
CAPITAL_STR	7077	6.910	1.210	2.000	8.000	6.000	7.000	8.000
SUPER_POW	7077	9.360	1.280	3.500	11.000	9.000	10.000	10.000
MONITOR	7077	7.170	1.590	4.000	10.000	5.000	8.000	8.000
Group by Countries								
BDI	55	6.330	2.610	0.000	10.000	5.000	7.000	8.000
CAPITAL_STR	55	5.820	1.120	3.000	8.000	5.350	6.000	6.590
SUPER_POW	55	8.480	1.610	3.500	11.000	7.920	8.670	9.860
MONITOR	55	8.210	1.020	6.000	10.000	7.440	8.140	9.000

The table presents further descriptive statistics. Specifically, Panel A shows descriptive statistics of our main variables grouped by countries, while Panel B shows descriptive statistics for variables used to construct each of *LOW_BDI*, *LOW_CAPITAL_STR*, *LOW_SUPER_POW* and *LOW_MONITOR*. *NCSKEW* is a negative conditional skewness of returns and *DUVOL* is a down-to-up volatility of returns; *DEPTH* is depth of credit information sharing index; *PRIV* is private credit bureau coverage (% of adult population); *PUB* is public credit registry coverage (% of adult population); *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *BDI* is a business extent of disclosure index; *CAPITAL_STR* is a capital stringency index; SUPER_POW is a supervisory power index; *MONITOR* is a private monitoring index; *LOW_BDI* is a dummy variable whose value is equal to one if a country has low business extent of disclosure index and zero otherwise: *LOW_CAPITAL_STR* is a dummy variable whose value is equal to one if a country has low capital stringency index and zero otherwise; *LOW_SUPER_POW* is a dummy variable whose value is equal to one if a country has low supervisory power index and zero otherwise; *LOW_MONITOR* is a dummy variable whose value is equal to one if a country has low private monitoring index and zero otherwise. Further detail of all variables is presented in Table 4-1 in this chapter. Obs is observation. Stdev is for standard deviation. Min is minimum. Max is maximum. P25 is 25th percentile of the sample. P50 is 50th percentile (or median) of the sample. P75 is 75th percentile of the sample.

Table 4-4: Mean Value of Negative Conditional Skewness, Credit Information Sharing Measures and Bank Regulatory Variables

Date	Obs.	Percent	*NCSKEW*	*DEPTH*	*PRIV*	*PUB*	*IFRS*	*BDI*	*CAPITAL _STR*	*SUPER _POW*	*MONITOR*
2006	953	12.60%	-0.4478	5.5761	0.8348	0.0516	0.9570	6.9864	6.5058	9.4485	5.3554
2007	873	11.54%	0.1233	5.5120	0.8023	0.0748	0.9255	6.9817	6.3919	9.3347	5.4289
2008	950	12.56%	0.1707	5.4916	0.7762	0.0835	0.8663	6.8937	6.2100	9.2580	5.5139
2009	977	12.92%	0.1307	5.4340	0.7497	0.1074	0.8700	6.9345	7.3255	9.4310	8.2379
2010	961	12.71%	-0.0429	5.4173	0.7415	0.1142	0.8626	6.8949	7.2761	9.3918	8.2623
2011	975	12.89%	0.1151	5.4215	0.7337	0.1283	0.8708	6.8636	7.2347	9.3571	8.2903
2012	959	12.68%	-0.2267	5.4307	0.7673	0.1674	0.8728	6.9009	7.2181	9.3364	8.3028
2013	914	12.09%	-0.3823	5.4354	0.7664	0.1939	0.8829	6.9497	7.1791	9.3472	8.2896
Total	**7562**	**100.00%**	**-0.0700**	**5.4648**	**0.7715**	**0.1150**	**0.8885**	**6.9257**	**6.9176**	**9.3631**	**7.2101**

The table presents the yearly sample mean of our main variables. *NCSKEW* is a negative conditional skewness of returns and *DUVOL* is a down-to-up volatility of returns; *DEPTH* is depth of credit information sharing index; *PRIV* is private credit bureau coverage (% of adult population); *PUB* is public credit registry coverage (% of adult population); *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *BDI* is a business extent of disclosure index; *CAPITAL_STR* is a capital stringency index; *SUPER_POW* is a supervisory power index; *MONITOR* is a private monitoring index. Further detail of all variables is presented in Table 4-1 in this chapter.

Table 4-5: Pearson Correlation Matrix

Variables	NCSKEW	DUVOL	DEPTH	PRIV	PUB	IFRS	LOW _BDI	LOW _CAPITAL _STR	LOW _SUPER _POW	LOW _MONITOR	DEPOSIT_INS	LOW_ ACTIVITY _RES
NCSKEW	1.000											
DUVOL	0.912	1.000										
DEPTH	0.047	0.071	1.000									
PRIV	0.065	0.092	0.772	1.000								
PUB	-0.063	-0.075	-0.193	-0.389	1.000							
IFRS	-0.004	0.005	-0.052	0.095	-0.060	1.000						
LOW_BDI	-0.027	-0.043	-0.422	-0.466	0.174	-0.048	1.000					
LOW_CAPITAL_STR	-0.046	-0.065	-0.610	-0.724	0.244	-0.263	0.311	1.000				
LOW_SUPER_POW	-0.021	-0.033	-0.521	-0.626	0.184	-0.275	0.384	0.727	1.000			
LOW_MONITOR	0.008	-0.003	0.032	-0.006	-0.105	-0.122	-0.070	0.048	0.008	1.000		
DEPOSIT_INS	0.003	0.011	0.243	0.278	-0.055	0.089	-0.204	-0.312	-0.299	-0.006	1.000	
LOW_ACTIVITY_RES	0.008	0.020	-0.055	-0.034	0.041	0.010	0.206	0.010	0.049	-0.698	0.030	1.000
DTURN	0.005	0.000	0.068	0.078	-0.021	0.040	-0.018	-0.071	-0.071	0.013	0.037	0.000
SIGMA	0.103	0.095	0.104	0.114	-0.084	0.124	-0.080	-0.167	-0.158	-0.347	0.076	0.342
MEAN	-0.094	-0.085	-0.063	-0.085	0.043	-0.067	0.054	0.101	0.089	0.121	-0.036	-0.128
MV	-0.016	-0.032	-0.222	-0.320	0.266	-0.218	0.233	0.342	0.403	0.047	-0.231	-0.065
MTBY	-0.014	-0.023	-0.086	-0.097	0.091	0.017	-0.010	0.076	-0.026	-0.005	0.003	0.005
LEV	0.037	0.037	0.121	0.056	0.040	-0.195	-0.045	0.045	0.124	0.021	0.028	-0.076
ROA	-0.107	-0.101	-0.131	-0.149	0.057	0.004	0.068	0.155	0.073	0.180	-0.106	-0.184
DEPOSIT	-0.011	0.005	0.299	0.233	-0.261	-0.174	-0.293	-0.249	-0.386	-0.006	0.026	-0.110
CAR_TIER1	-0.050	-0.049	-0.091	-0.032	-0.047	0.131	0.055	-0.003	-0.071	-0.088	-0.007	0.124
C_SCORE	-0.058	-0.017	0.126	0.143	-0.097	0.043	-0.058	-0.099	-0.133	-0.202	0.107	0.272
GDPG	-0.071	-0.067	-0.353	-0.382	0.101	0.025	0.117	0.361	0.250	0.213	-0.327	-0.345
MKTCAP	0.034	0.057	0.376	0.402	-0.230	0.181	-0.220	-0.387	-0.408	0.362	0.081	-0.355
GDPPC	0.090	0.116	0.466	0.671	-0.231	0.110	-0.244	-0.543	-0.359	0.057	0.253	0.159
CORRUPTION	0.078	0.103	0.338	0.490	-0.277	0.021	-0.265	-0.329	-0.185	0.163	0.287	0.093

GOV_EFF	0.084	0.110	0.469	0.608	-0.285	0.074	-0.368	-0.462	-0.321	0.185	0.337	0.025
POLITIC	0.072	0.099	0.337	0.482	-0.153	-0.039	-0.199	-0.318	-0.216	0.046	0.308	0.147
REG_QUA	0.082	0.108	0.483	0.651	-0.277	0.182	-0.333	-0.529	-0.367	0.235	0.354	-0.001
RULE_LAW	0.084	0.112	0.503	0.659	-0.322	0.155	-0.331	-0.521	-0.362	0.106	0.356	0.063
VOICE_ACC	0.060	0.080	0.486	0.574	-0.259	0.156	-0.313	-0.390	-0.247	0.115	0.501	0.059
LEGALORIGIN	0.023	0.046	0.583	0.586	-0.336	0.338	-0.425	-0.630	-0.625	-0.005	0.102	-0.113
ETHNIC_FRAC	-0.032	-0.028	0.172	0.053	-0.053	0.370	-0.185	-0.237	-0.337	-0.094	0.041	-0.108
LATITUDE	0.065	0.065	0.079	0.174	-0.205	0.094	0.028	-0.126	0.121	0.066	0.262	0.029

The table presents correlation matrix between variables. *NCSKEW* is a negative conditional skewness of returns and *DUVOL* is a down-to-up volatility of returns; *DEPTH* is depth of credit information sharing index; *PRIV* is private credit bureau coverage (% of adult population); *PUB* is public credit registry coverage (% of adult population); *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *LOW_BDI* is a dummy variable whose value is equal to one if a country has low business extent of disclosure index and zero otherwise: *LOW_CAPITAL_STR* is a dummy variable whose value is equal to one if a country has low capital stringency index and zero otherwise; *LOW_SUPER_POW* is a dummy variable whose value is equal to one if a country has low supervisory power index and zero otherwise; *LOW_MONITOR* is a dummy variable whose value is equal to one if a country has low private monitoring index and zero otherwise; *DEPOSIT_INS* is a dummy variable whose value is equal to one when there exist deposit insurance regime in the country; *LOW_ACTIVITY_RES* is a dummy variable whose value is equal to one if a country has low activity restriction index and zero otherwise; *DTURN* the detrended average monthly stock turnover; *SIGMA* is the standard deviation of firm-specific weekly return over the year; *MEAN* is the average arithmetic mean of firm-specific weekly return over the year; *MV* is the market value of equity; *MTBV* is the natural logarithm of the market value of equity divided by the value of equity; *LEV* is the leverage ratio calculated as total liability to total assets; *ROA* is a return on assets calculated as income before extraordinary items divided by total assets; *CAR_TIER1* is a tier1 capital adequacy ratio; *DEPOSIT* is a ratio of total deposits to total assets; *C_SCORE* is a measure of accounting conservatism; *GDPG* is real GDP growth; *MKTCAP* is the stock market capitalization scaled by GDP; *GDPPC* is the natural logarithm of GDP per capital; *CORRUPTION* is a control of corruption index; *GOV_EFF* is a government effectiveness index; *POLITIC* is a political stability index; *REG_QUA* is a regulatory quality index; *RULE_LAW* is a rule of law index; *VOICE_ACC* is a voice and accountability index; *LEGALORIGIN* is a dummy variable whose value is equal to one if a country has English legal origin; *ETHNIC_FRAC* is an ethnic fractionalization; *LATITUDE* is a country's latitude scaled to take a value between zero and one. Further detail of all variables are presented in Table 4-1 in this chapter.

Table 4-6: Pearson Correlation Matrix (Continued)

Variables	*DTURN*	*SIGMA*	*MEAN*	*MV*	*MTBY*	*LEV*	*ROA*	*DEPOSIT*	*CAR_TIER1*	*C_SCORE*	*GDPG*
DTURN	1.000										
SIGMA	0.104	1.000									
MEAN	-0.042	-0.516	1.000								
MV	-0.019	-0.403	0.272	1.000							
MTBY	-0.005	-0.001	0.019	0.037	1.000						
LEV	0.010	0.140	-0.119	0.055	0.001	1.000					
ROA	-0.065	-0.477	0.412	0.270	0.031	-0.282	1.000				
DEPOSIT	-0.006	0.132	-0.052	-0.382	0.026	0.100	-0.068	1.000			
CAR_TIER1	-0.029	-0.118	0.108	-0.082	0.014	-0.713	0.240	-0.081	1.000		
C_SCORE	-0.029	0.107	-0.052	-0.209	-0.005	0.027	-0.083	0.138	0.028	1.000	
GDPG	-0.103	-0.296	0.196	0.203	0.066	-0.114	0.315	0.029	0.080	0.088	1.000
MKTCAP	0.037	-0.121	0.035	-0.111	-0.063	-0.087	0.093	0.202	0.052	0.163	0.134
GDPPC	0.080	0.043	-0.080	-0.224	-0.115	0.019	-0.143	-0.060	-0.036	0.100	-0.468
CORRUPTION	0.057	-0.026	-0.057	-0.190	-0.113	0.100	-0.096	-0.050	-0.071	0.062	-0.370
GOV_EFF	0.071	0.010	-0.069	-0.257	-0.118	0.089	-0.119	0.037	-0.072	0.089	-0.395
POLITIC	0.058	-0.036	-0.039	-0.108	-0.087	0.104	-0.092	-0.065	-0.076	0.121	-0.358
REG_QUA	0.081	0.008	-0.070	-0.247	-0.117	0.052	-0.116	-0.050	-0.068	0.041	-0.422
RULE_LAW	0.072	0.057	-0.094	-0.293	-0.131	0.079	-0.141	0.026	-0.070	0.108	-0.422
VOICE_ACC	0.062	0.049	-0.067	-0.251	-0.074	0.198	-0.153	-0.032	-0.125	0.101	-0.497
LEGALORIGIN	0.055	0.171	-0.086	-0.339	-0.067	-0.138	-0.039	0.321	0.055	0.151	0.011
ETHNIC_FRAC	0.007	0.135	-0.032	-0.164	0.073	-0.174	0.078	0.290	0.139	0.089	0.321
LATITUDE	-0.001	0.033	-0.045	-0.114	-0.131	0.117	-0.122	-0.193	-0.084	0.060	-0.308

The table presents correlation matrix between variables. *NCSKEW* is a negative conditional skewness of returns and *DUVOL* is a down-to-up volatility of returns; *DEPTH* is depth of credit information sharing index; *PRIV* is private credit bureau coverage (% of adult population); *PUB* is public credit registry coverage (% of adult population); *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *LOW_BDI* is a dummy variable whose value is equal to one if a country has low business extent of disclosure index and zero otherwise: *LOW_CAPITAL_STR* is a dummy variable whose value is equal to one if a country has low capital stringency index and zero otherwise; *LOW_SUPER_POW* is a dummy variable whose value is equal to one if a country has low supervisory power index and zero otherwise; *LOW_MONITOR* is a dummy variable whose value is equal to one if a country has low private monitoring index and zero otherwise; *DEPOSIT_INS* is a dummy variable whose value is equal to one when there exist deposit insurance regime in the country; *DTURN* the detrended average monthly stock turnover; *SIGMA* is the standard deviation of firm-specific weekly return over the year; *MEAN* is the average arithmetic mean of firm-specific weekly return over the year; *MV* is the market value of equity; *MTBV* is the natural logarithm of the market value of equity divided by the value of equity; *LEV* is the leverage ratio calculated as total liability to total assets; *ROA* is a return on assets calculated as income before extraordinary items divided by total assets; *CAR_TIER1* is a tier1 capital adequacy ratio; *DEPOSIT* is a ratio of total deposits to total assets; *C_SCORE* is a measure of accounting conservatism; *GDPG* is real GDP growth; *MKTCAP* is the stock market capitalization scaled by GDP; *GDPPC* is the natural logarithm of GDP per capital; *CORRUPTION* is a control of corruption index; *GOV_EFF* is a government effectiveness index; *POLITIC* is a political stability index; *REG_QUA* is a regulatory quality index; *RULE_LAW* is a rule of law index; *VOICE_ACC* is a voice and accountability index; *LEGALORIGIN* is a dummy variable whose value is equal to one if a country has English legal origin; *ETHNIC_FRAC* is an ethnic fractionalization; *LATITUDE* is a country's latitude scaled to take a value between zero and one. Further detail of all variables are presented in Table 4-1 in this chapter.

Table 4-7: Pearson Correlation Matrix (Continued)

Variables	*MKTCAP*	*GDPPC*	*CORRUPTION*	*GOV_EFF*	*POLITIC*	*REG_QUA*	*RULE_LAW*	*VOICE_ACC*	*LEGALORIGIN*	*ETHNIC_FRAC*	*LATITUDE*
MKTCAP	1.000										
GDPPC	0.301	1.000									
CORRUPTION	0.330	0.850	1.000								
GOV_EFF	0.439	0.857	0.953	1.000							
POLITIC	0.242	0.854	0.861	0.816	1.000						
REG_QUA	0.442	0.891	0.911	0.949	0.794	1.000					
RULE_LAW	0.432	0.883	0.944	0.967	0.828	0.950	1.000				
VOICE_ACC	0.236	0.696	0.791	0.798	0.702	0.803	0.827	1.000			
LEGALORIGIN	0.571	0.168	0.102	0.272	-0.050	0.298	0.331	0.174	1.000		
ETHNIC_FRAC	0.390	-0.385	-0.410	-0.243	-0.473	-0.253	-0.231	-0.267	0.723	1.000	
LATITUDE	-0.112	0.488	0.445	0.409	0.410	0.402	0.435	0.417	-0.198	-0.436	1.000

The table presents correlation matrix between variables. *NCSKEW* is a negative conditional skewness of returns and *DUVOL* is a down-to-up volatility of returns; *DEPTH* is depth of credit information sharing index; *PRIV* is private credit bureau coverage (% of adult population); *PUB* is public credit registry coverage (% of adult population); *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *LOW_BDI* is a dummy variable whose value is equal to one if a country has low business extent of disclosure index and zero otherwise: *LOW_CAPITAL_STR* is a dummy variable whose value is equal to one if a country has low capital stringency index and zero otherwise; *LOW_SUPER_POW* is a dummy variable whose value is equal to one if a country has low supervisory power index and zero otherwise; *LOW_MONITOR* is a dummy variable whose value is equal to one if a country has low private monitoring index and zero otherwise; *DEPOSIT_INS* is a dummy variable whose value is equal to one when there exist deposit insurance regime in the country; *DTURN* the detrended average monthly stock turnover; *SIGMA* is the standard deviation of firm-specific weekly return over the year; *MEAN* is the average arithmetic mean of firm-specific weekly return over the year; *MV* is the market value of equity; *MTBV* is the natural logarithm of the market value of equity divided by the value of equity; *LEV* is the leverage ratio calculated as total liability to total assets; *ROA* is a return on assets calculated as income before extraordinary items divided by total assets; *CAR_TIER1* is a tier1 capital adequacy ratio; *DEPOSIT* is a ratio of total deposits to total assets; *C_SCORE* is a measure of accounting conservatism; *GDPG* is real GDP growth; *MKTCAP* is the stock market capitalization scaled by GDP; *GDPPC* is the natural logarithm of GDP per capital; *CORRUPTION* is a control of corruption index; *GOV_EFF* is a government effectiveness index; *POLITIC* is a political stability index; *REG_QUA* is a regulatory quality index; *RULE_LAW* is a rule of law index; *VOICE_ACC* is a voice and accountability index; *LEGALORIGIN* is a dummy variable whose value is equal to one if a country has English legal origin; *ETHNIC_FRAC* is an ethnic fractionalization; *LATITUDE* is a country's latitude scaled to take a value between zero and one. Further detail of all variables are presented in Table 4-1 in this chapter.

Table 4-8: Model Selection and Diagnostic Tests

Panel A: Poolability Test

F(1401, 6147)	1.62
F(1401, 6147) P-value	0.00

The test of poolability is performed to determine the presence of individual effects, α_i in the regression model. H_0: α_i=0 for i = 1, 2, 3…., N. The rejection of the null hypothesis indicates that the individual effects exist and the OLS estimates suffer from the problem of omitted variables.

Panel B: Hausman Test

Chi-sq(13)	271.72
Chi-sq(13) P-value	0.00

The Hausman test is performed to choose between the fixed effect model and the random effect model. H_0: difference in coefficients not systemic. The rejection of the null hypothesis indicates that the fix effect regression model is preferable to the random effect.

Panel C: Modified Wald Test for Groupwise Heteroskedasticity in Fixed Effect Regression Model

Chi-sq(1402)	713.4
Chi-sq(1402) P-value	0.00

The modified Wald test is performed to test for the presence of groupwise heteroskedasticity in the residuals. H_0: $\sigma_i^2 = \sigma^2$ for i = 1, 2, 3…., Ng, where Ng is the number of cross-sectional units. The rejection of the null hypothesis indicates that there exist the groupwise geteroskedasticity.

Panel D: Wooldridge Test for Autocorrelation in Panel Data

F(1, 1114)	40.807
F(1, 1114) P-value	0.00

The Wooldridge test is performed to test for the presence of serial correlation. H_0: no first-order autocorrelation. The rejection of the null hypothesis indicates that data does not have first-order autocorrelation.

Table 4-9: The Impact of Credit Information Sharing Measures on Bank Stock Price Crash Risk

Variable	NCSKEW		
	(1)	(2)	(3)
DEPTH	-0.009		
	(-0.30)		
PRIV		0.028	
		(0.32)	
PUB			-0.462***
			(-2.72)
DTURN	0.001**	0.001*	0.001*
	(2.08)	(1.97)	(1.76)
SIGMA	3.064***	3.017***	2.972***
	(3.54)	(3.53)	(3.53)
MEAN	-3.821	-3.862	-4.005*
	(-1.56)	(-1.59)	(-1.68)
MV	0.030***	0.030***	0.032***
	(3.05)	(3.02)	(3.15)
MTBV	-0.024***	-0.023**	-0.011
	(-2.69)	(-2.64)	(-1.13)
LEV	-0.196	-0.222	-0.195
	(-0.38)	(-0.42)	(-0.39)
ROA	-4.566***	-4.572***	-4.536***
	(-5.97)	(-5.97)	(-5.70)
CAR_TIER1	-0.001	-0.001	-0.001
	(-0.19)	(-0.22)	(-0.37)
DEPOSIT	0.119	0.092	0.034
	(0.77)	(0.67)	(0.25)
GDPG	-0.775	-0.573	-0.635
	(-0.62)	(-0.48)	(-0.53)
MKTCAP	0.002	-0.012	-0.017
	(0.03)	(-0.18)	(-0.29)
GDPPC	0.095***	0.089**	0.085***
	(3.36)	(2.63)	(3.21)
Constant	-1.889***	-1.837***	-1.775***
	(-3.31)	(-2.89)	(-3.28)
R-squared	0.061	0.061	0.063
Bank Fixed Effects	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes
Observations	7,562	7,562	7,562

This table presents the regression for the impact of credit information sharing on crash risk. The dependent variable is crash stock measured by *NCSKEW*. *NCSKEW* is a negative conditional skewness of returns; *DEPTH* is depth of credit information sharing index; *PRIV* is private credit bureau coverage (% of adult population); *PUB* is public credit registry coverage (% of adult population); *DTURN* the detrended average monthly stock turnover; *SIGMA* is the standard deviation of firm-specific weekly return over the year; *MEAN* is the average arithmetic mean of firm-specific weekly return over the year; *MV* is the market value of equity; *MTBV* is the natural logarithm of the market value of equity divided by the value of equity; *LEV* is the leverage ratio calculated as total liability to total assets; *ROA* is a return on assets calculated as income before extraordinary items divided by total assets; *CAR_TIER1* is a tier1 capital adequacy ratio; *DEPOSIT* is a ratio of total deposits to total assets; *GDPG* is real GDP growth; *MKTCAP* is the stock market capitalization scaled by GDP; *GDPPC* is the natural logarithm of GDP per capital. Further detail of all variables are presented in Table 4-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 4-10: The Impact of Public Credit Registry Coverages on Bank Stock Price Crash Risk: The Role of Information Asymmetry

Variable	***NCSKEW***		***NCSKEW***	
	(1)	**(2)**	**(3)**	**(4)**
PUB	-0.464***	-0.870***	-0.461***	-0.413*
	(-2.69)	(-6.91)	(-2.72)	(-1.70)
IFRS	-0.022*	-0.052		
	(-1.77)	(-1.17)		
IFRS * PUB		0.510*		
		(1.91)		
LOW_BDI			-0.012	-0.002
			(-0.17)	(-0.03)
LOW_BDI * PUB				-0.121
				(-0.40)
DTURN	0.001*	0.001*	0.001*	0.001*
	(1.81)	(1.84)	(1.71)	(1.72)
SIGMA	3.007***	2.989***	2.967***	2.980***
	(3.51)	(3.53)	(3.55)	(3.56)
MEAN	-4.008*	-3.986*	-4.005*	-3.994*
	(-1.68)	(-1.68)	(-1.68)	(-1.68)
MV	0.031***	0.030***	0.032***	0.032***
	(2.97)	(2.87)	(3.14)	(3.13)
MTBV	-0.01	-0.012	-0.011	-0.013
	(-0.92)	(-1.14)	(-1.15)	(-1.18)
LEV	-0.221	-0.258	-0.195	-0.199
	(-0.44)	(-0.51)	(-0.39)	(-0.40)
ROA	-4.512***	-4.532***	-4.537***	-4.533***
	(-5.59)	(-5.67)	(-5.69)	(-5.71)
CAR_TIER1	-0.001	-0.002	-0.001	-0.001
	(-0.39)	(-0.45)	(-0.37)	(-0.39)
DEPOSIT	0.018	0.003	0.028	0.032
	(0.13)	(0.02)	(0.20)	(0.23)
GDPG	-0.621	-0.616	-0.627	-0.662
	(-0.52)	(-0.52)	(-0.53)	(-0.55)
MKTCAP	-0.012	0.011	-0.018	-0.017
	(-0.21)	(0.18)	(-0.31)	(-0.30)
GDPPC	0.085***	0.081***	0.084***	0.085***
	(3.21)	(3.07)	(3.04)	(3.04)
Constant	-1.707***	-1.588***	-1.764***	-1.775***
	(-2.90)	(-2.72)	(-3.19)	(-3.18)
R-squared	0.063	0.063	0.063	0.063
Bank Fixed Effects	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
Observations	7,562	7,562	7,562	7,562

This table presents the regression for the impact of information asymmetry on the relationship between public credit registry coverages and crash risk. The dependent variable is crash stock measured by *NCSKEW*. *NCSKEW* is a negative conditional skewness of returns; *PUB* is public credit registry coverage (% of adult population); *IFRS* and *BDI* are proxies of information environment; *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *LOW_BDI* is a dummy variable whose value is equal to one if a country has low business extent of disclosure index and zero otherwise; *DTURN* the detrended average monthly stock turnover; *SIGMA* is the standard deviation of firm-specific weekly return over the year; *MEAN* is the average arithmetic mean of firm-specific weekly return over the year; *MV* is the market value of equity; *MTBV* is the natural logarithm of the market value of equity divided by the value of equity; *LEV* is the leverage ratio calculated as total liability to total assets; *ROA* is a return on assets calculated as income before extraordinary items divided by total assets; *CAR_TIER1* is a tier1 capital adequacy ratio; *DEPOSIT* is a ratio of total deposits to total assets; *GDPG* is real GDP growth; *MKTCAP* is the stock market capitalization scaled by GDP; *GDPPC* is the natural logarithm of GDP per capital. Further detail of all variables are presented in Table 4-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 4-11: The Impact of Public Credit Registry Coverages on Bank Stock Price Crash Risk: The Role of Bank Regulations

Variable	*NCSKEW*		*NCSKEW*		*NCSKEW*	
	(1)	(2)	(3)	(4)	(5)	(6)
PUB	-0.481***	-0.454**	-0.463**	-0.436**	-0.465**	-0.465**
	(-2.78)	(-2.53)	(-2.57)	(-2.40)	(-2.63)	(-2.63)
LOW_CAPITAL_STR	0.226*	-0.09				
	(1.89)	(-0.49)				
LOW_CAPITAL_STR * PUB		-3.389***				
		(-3.55)				
LOW_SUPER_POW			0.016	0.138		
			(0.13)	(1.17)		
LOW_SUPER_POW * PUB				-5.124***		
				(-3.69)		
LOW_MONITOR					0.041*	0.074
					(1.71)	-0.85
LOW_MONITOR * PUB						-4.146***
						(-8.08)
DTURN	0.001	0.001	0.001	0.002	0.001	0.001
	(0.13)	(0.14)	(0.11)	(0.22)	(0.12)	(0.16)
SIGMA	3.247***	3.293***	3.170***	3.180***	3.205***	3.319***
	(3.23)	(3.21)	(3.33)	(3.38)	(3.32)	(3.32)
MEAN	-4.012*	-3.938	-4.036*	-3.967*	-3.993*	-3.765
	(-1.71)	(-1.65)	(-1.72)	(-1.68)	(-1.70)	(-1.53)
MV	0.029**	0.029**	0.029**	0.028**	0.029**	0.031***
	(2.62)	(2.64)	(2.62)	(2.57)	(2.66)	(2.74)
MTBV	-0.004	-0.007	-0.009	-0.01	-0.009	-0.01
	(-0.34)	(-0.6)	(-0.88)	(-0.98)	(-0.88)	(-1.07)
LEV	-0.144	-0.133	-0.237	-0.311	-0.21	-0.228
	(-0.31)	(-0.29)	(-0.51)	(-0.65)	(-0.45)	(-0.47)
ROA	-4.604***	-4.630***	-4.593***	-4.578***	-4.612***	-4.640***
	(-5.82)	(-5.92)	(-5.82)	(-5.68)	(-5.83)	(-5.75)
CAR_TIER1	-0.001	-0.001	-0.002	-0.003	-0.002	-0.002
	(-0.29)	(-0.18)	(-0.53)	(-0.70)	(-0.49)	(-0.63)
DEPOSIT	-0.098	-0.081	-0.098	-0.102	-0.11	-0.142
	(-0.64)	(-0.52)	(-0.63)	(-0.65)	(-0.72)	(-0.93)
GDPG	-0.516	-0.487	-0.517	-0.372	-0.513	-0.468
	(-0.46)	(-0.43)	(-0.44)	(-0.33)	(-0.47)	(-0.42)
MKTCAP	0.006	-0.001	0.021	-0.005	0.015	-0.018
	(0.11)	(-0.02)	(0.37)	(-0.08)	(0.25)	(-0.32)
GDPPC	0.072***	0.071***	0.077***	0.084***	0.077***	0.079***
	(3.09)	(3.05)	(3.07)	(3.45)	(3.26)	(3.48)
Constant	-1.577**	-1.588**	-1.550***	-1.500**	-1.601***	-1.595***
	(-2.66)	(-2.66)	(-2.68)	(-2.58)	(-2.69)	(-2.68)
R-squared	0.067	0.068	0.067	0.068	0.067	0.068
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,077	7,077	7,077	7,077	7,077	7,077

This table presents the regression for the impact of bank regulations on the relationship between public credit registry coverages and crash risk. The dependent variable is crash stock measured by *NCSKEW*. *NCSKEW* is a negative conditional skewness of returns; *PUB* is public credit registry coverage (% of adult population); *LOW_CAPITAL_STR* is a dummy variable whose value is equal to one if a country has low capital stringency index and zero otherwise; *LOW_SUPER_POW* is a dummy variable whose value is equal to one if a country has low supervisory power index and zero otherwise; *LOW_MONITOR* is a dummy variable whose value is equal to one if a country has low private monitoring index and zero otherwise; *DTURN* the detrended average monthly stock turnover; *SIGMA* is the standard deviation of firm-specific weekly return over the year; *MEAN* is the average arithmetic mean of firm-specific weekly return over the year; *MV* is the market value of equity; *MTBV* is the natural logarithm of the market value of equity divided by the value of equity; *LEV* is the leverage ratio calculated as total liability to total assets; *ROA* is a return on assets calculated as income before extraordinary items divided by total assets; *CAR_TIER1* is a tier1 capital adequacy ratio; *DEPOSIT* is a ratio of total deposits to total assets; *GDPG* is real GDP growth; *MKTCAP* is the stock market capitalization scaled by GDP; *GDPPC* is the natural logarithm of GDP per capital. Further detail of all variables are presented in Table 4-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 4-12: The Impact of Credit Information Sharing Measures on Bank Stock Price Crash Risk - DUVOL

Variable	*DUVOL*		
	(1)	(2)	(3)
DEPTH	0.003		
	(0.26)		
PRIV		0.024	
		(0.70)	
PUB			-0.199***
			(-2.97)
DTURN	0.001***	0.001***	0.001***
	(3.44)	(3.36)	(3.30)
SIGMA	1.049***	1.034***	1.025***
	(3.44)	(3.45)	(3.41)
MEAN	-0.565	-0.580	-0.631
	(-1.10)	(-1.14)	(-1.24)
MV	0.007	0.008	0.008
	(1.42)	(1.42)	(1.51)
MTBV	-0.017***	-0.017***	-0.012***
	(-4.72)	(-4.89)	(-3.23)
LEV	-0.056	-0.061	-0.045
	(-0.27)	(-0.29)	(-0.23)
ROA	-1.592***	-1.589***	-1.574***
	(-6.49)	(-6.43)	(-6.30)
CAR_TIER1	-0.001	-0.001	-0.002
	(-0.96)	(-0.99)	(-1.12)
DEPOSIT	0.030	0.023	0.004
	(0.55)	(0.48)	(0.07)
GDPG	0.082	0.119	0.058
	(0.27)	(0.38)	(0.21)
MKTCAP	0.024	0.021	0.022
	(1.11)	(0.91)	(1.24)
GDPPC	0.046***	0.042***	0.043***
	(5.16)	(4.01)	(5.53)
Constant	-0.838***	-0.796***	-0.790***
	(-3.23)	(-2.95)	(-3.19)
R-squared	0.049	0.049	0.051
Bank Fixed Effects	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes
Observations	7,562	7,562	7,562

This table presents the regression for the impact of credit information sharing on crash risk. The dependent variable is crash stock measured by *DUVOL*. *DUVOL* is a down-to-up volatility of returns; *DEPTH* is depth of credit information sharing index; *PRIV* is private credit bureau coverage (% of adult population); *PUB* is public credit registry coverage (% of adult population); *DTURN* the detrended average monthly stock turnover; *SIGMA* is the standard deviation of firm-specific weekly return over the year; *MEAN* is the average arithmetic mean of firm-specific weekly return over the year; *MV* is the market value of equity; *MTBV* is the natural logarithm of the market value of equity divided by the value of equity; *LEV* is the leverage ratio calculated as total liability to total assets; *ROA* is a return on assets calculated as income before extraordinary items divided by total assets; *CAR_TIER1* is a tier1 capital adequacy ratio; *DEPOSIT* is a ratio of total deposits to total assets; *GDPG* is real GDP growth; *MKTCAP* is the stock market capitalization scaled by GDP; *GDPPC* is the natural logarithm of GDP per capital. Further detail of all variables are presented in Table 4-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 4-13: The Effect of Information Asymmetry on the Linkage between Public Credit Registry Coverages and Bank Stock Price Crash Risk - DUVOL

Variable	*DUVOL*		*DUVOL*	
	(1)	(2)	(3)	(4)
PUB	-0.199***	-0.335***	-0.198***	-0.189*
	(-2.97)	(-7.19)	(-3.00)	(-1.90)
IFRS	-0.001*	-0.011		
	(-2.10)	(-0.67)		
IFRS * PUB		0.171*		
		(1.73)		
LOW_BDI			-0.016	-0.014
			(-0.75)	(-0.58)
LOW_BDI * PUB				-0.023
				(-0.20)
DTURN	0.001***	0.001***	0.001***	0.001***
	(3.52)	(3.64)	(3.19)	(3.18)
SIGMA	1.027***	1.021***	1.018***	1.021***
	(3.45)	(3.45)	(3.43)	(3.43)
MEAN	-0.632	-0.624	-0.631	-0.629
	(-1.24)	(-1.23)	(-1.24)	(-1.23)
MV	0.008	0.008	0.009	0.009
	(1.43)	(1.36)	(1.52)	(1.51)
MTBV	-0.012***	-0.013***	-0.013***	-0.013***
	(-2.92)	(-3.01)	(-3.24)	(-3.02)
LEV	-0.047	-0.059	-0.045	-0.046
	(-0.23)	(-0.30)	(-0.23)	(-0.23)
ROA	-1.573***	-1.579***	-1.577***	-1.576***
	(-6.31)	(-6.46)	(-6.40)	(-6.40)
CAR_TIER1	-0.002	-0.002	-0.002	-0.002
	(-1.11)	(-1.17)	(-1.12)	(-1.13)
DEPOSIT	0.002	-0.003	-0.005	-0.004
	(0.05)	(-0.05)	(-0.09)	(-0.08)
GDPG	0.059	0.06	0.068	0.061
	(0.21)	(0.22)	(0.24)	(0.22)
MKTCAP	0.022	0.03	0.021	0.021
	(1.19)	(1.55)	(1.13)	(1.13)
GDPPC	0.043***	0.042***	0.042***	0.042***
	(5.52)	(5.34)	(5.27)	(5.10)
Constant	-0.786***	-0.746***	-0.775***	-0.778***
	(-2.96)	(-2.82)	(-3.14)	(-3.12)
R-squared	0.051	0.051	0.051	0.051
Bank Fixed Effects	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
Observations	7,562	7,562	7,562	7,562

This table presents the regression for the impact of information asymmetry on the relationship between public credit registry coverages and crash risk. The dependent variable is crash stock measured by *DUVOL*. *DUVOL* is a down-to-up volatility of returns; *PUB* is public credit registry coverage (% of adult population); *IFRS* and *BDI* are proxies of information environment; *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *LOW_BDI* is a dummy variable whose value is equal to one if a country has low business extent of disclosure index and zero otherwise; *DTURN* the detrended average monthly stock turnover; *SIGMA* is the standard deviation of firm-specific weekly return over the year; *MEAN* is the average arithmetic mean of firm-specific weekly return over the year; *MV* is the market value of equity; *MTBV* is the natural logarithm of the market value of equity divided by the value of equity; *LEV* is the leverage ratio calculated as total liability to total assets; *ROA* is a return on assets calculated as income before extraordinary items divided by total assets; *CAR_TIER1* is a tier1 capital adequacy ratio; *DEPOSIT* is a ratio of total deposits to total assets; *GDPG* is real GDP growth; *MKTCAP* is the stock market capitalization scaled by GDP; *GDPPC* is the natural logarithm of GDP per capital. Further detail of all variables are presented in Table 4-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

* indicates significance at the 10% level

** indicates significance at the 5% level

*** indicates significance at the 1% level

Table 4-14: The Effect of Bank Regulations on the Linkage between Public Credit Registry Coverages and Bank Stock Price Crash Risk - DUVOL

Variable	*DUVOL*		*DUVOL*		*DUVOL*	
	(1)	(2)	(3)	(4)	(5)	(6)
PUB	-0.207***	-0.201***	-0.199***	-0.193***	-0.201***	-0.201***
	(-3.01)	(-2.87)	(-2.77)	(-2.67)	(-2.86)	(-2.86)
LOW_CAPITAL_STR	0.102*	-0.069				
	(1.84)	(-1.26)				
LOW_CAPITAL_STR * PUB		-0.811***				
		(-2.83)				
LOW_SUPER_POW			0.007	0.037		
			(0.17)	(0.81)		
LOW_SUPER_POW * PUB				-1.264**		
				(-2.54)		
LOW_MONITOR					0.003*	0.01
					(1.90)	(0.35)
LOW_MONITOR * PUB						-0.968***
						(-4.75)
DTURN	0.001	0.001	0.001	0.001	0.001	0.001
	(0.30)	(0.30)	(0.32)	(0.29)	(0.31)	(0.30)
SIGMA	1.102***	1.113***	1.067***	1.070***	1.072***	1.099***
	(3.22)	(3.21)	(3.34)	(3.37)	(3.29)	(3.31)
MEAN	-0.543	-0.525	-0.554	-0.537	-0.549	-0.496
	(-1.03)	(-0.99)	(-1.05)	(-1.01)	(-1.02)	(-0.91)
MV	0.008	0.008	0.008	0.008	0.008	0.008
	(1.33)	(1.33)	(1.27)	(1.24)	(1.31)	(1.34)
MTBV	-0.009**	-0.006	-0.011***	-0.011***	-0.011***	-0.011***
	(-2.10)	(-1.61)	(-2.80)	(-2.84)	(-2.80)	(-2.91)
LEV	-0.02	-0.018	-0.063	-0.081	-0.06	-0.064
	(-0.10)	(-0.09)	(-0.32)	(-0.41)	(-0.30)	(-0.31)
ROA	-1.605***	-1.611***	-1.600***	-1.596***	-1.602***	-1.608***
	(-6.74)	(-6.84)	(-6.74)	(-6.54)	(-6.82)	(-6.80)
CAR_TIER1	-0.001	-0.001	-0.002	-0.002	-0.002	-0.002
	(-0.96)	(-0.88)	(-1.24)	(-1.33)	(-1.23)	(-1.28)
DEPOSIT	-0.027	-0.022	-0.026	-0.027	-0.029	-0.036
	(-0.49)	(-0.41)	(-0.49)	(-0.51)	(-0.53)	(-0.68)
GDPG	-0.017	-0.01	-0.017	-0.018	-0.029	-0.019
	(-0.06)	(-0.03)	(-0.06)	(-0.06)	(-0.10)	(-0.06)
MKTCAP	0.027	0.025	0.034*	0.027	0.033*	0.026
	(1.57)	(1.44)	(1.9)	(1.52)	(1.84)	(1.5)
GDPPC	0.037***	0.037***	0.040***	0.041***	0.039***	0.040***
	(5.3)	(5.23)	(4.95)	(5.26)	(5.07)	(5.21)
Constant	-0.731***	-0.734***	-0.719***	-0.707***	-0.721**	-0.719**
	(-2.68)	(-2.68)	(-2.73)	(-2.72)	(-2.60)	(-2.61)
R-squared	0.055	0.055	0.054	0.055	0.054	0.054
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,077	7,077	7,077	7,077	7,077	7,077

This table presents the regression for the impact of bank regulations on the relationship between public credit registry coverages and crash risk. The dependent variable is crash stock measured by *DUVOL*. *DUVOL* is a down-to-up volatility of returns; *PUB* is public credit registry coverage (% of adult population); *LOW_CAPITAL_STR* is a dummy variable whose value is equal to one if a country has low capital stringency index and zero otherwise; *LOW_SUPER_POW* is a dummy variable whose value is equal to one if a country has low supervisory power index and zero otherwise; *LOW_MONITOR* is a dummy variable whose value is equal to one if a country has low private monitoring index and zero otherwise; *DTURN* the detrended average monthly stock turnover; *SIGMA* is the standard deviation of firm-specific weekly return over the year; *MEAN* is the average arithmetic mean of firm-specific weekly return over the year; *MV* is the market value of equity; *MTBV* is the natural logarithm of the market value of equity divided by the value of equity; *LEV* is the leverage ratio calculated as total liability to total assets; *ROA* is a return on assets calculated as income before extraordinary items divided by total assets; *CAR_TIER1* is a tier1 capital adequacy ratio; *DEPOSIT* is a ratio of total deposits to total assets; *GDPG* is real GDP growth; *MKTCAP* is the stock market capitalization scaled by GDP; *GDPPC* is the natural logarithm of GDP per capital. Further detail of all variables are presented in Table 4-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

*   indicates significance at the 10% level
**   indicates significance at the 5% level
*** indicates significance at the 1% level

Table 4-15: Subsample Analysis for the Impact of Public Credit Registry Coverages on Bank Stock Price Crash Risk - grouped by Information Asymmetry

Variable	*NCSKEW*	
	IFRS Adoption	***NON-IFRS Adoption***
	(1)	**(2)**
PUB	-0.341	-0.782*
	(-1.59)	(-2.16)
DTURN	0.020***	0.01
	(4.08)	(1.52)
SIGMA	2.909***	2.123
	(3.38)	(0.74)
MEAN	-4.568**	11.073
	(-2.22)	(1.15)
MV	0.030**	0.015
	(2.53)	(0.38)
MTBV	-0.013	2.729
	(-1.36)	(1.3)
LEV	-0.45	1.447
	(-0.84)	(0.57)
ROA	-4.748***	2.512
	(-5.81)	(0.86)
CAR_TIER1	-0.003	0.012
	(-0.79)	(0.92)
DEPOSIT	-0.019	0.091
	(-0.12)	(0.18)
GDPG	-0.428	-1.944
	(-0.35)	(-0.77)
MKTCAP	0.025	0.076
	(0.39)	(0.52)
GDPPC	0.079***	0.054
	(2.89)	(0.52)
Constant	-1.461**	-2.557
	(-2.50)	(-0.95)
R-squared	0.069	0.067
Bank Fixed Effects	Yes	Yes
Time Dummies	Yes	Yes
Observations	6,715	847

This table presents the regression for the impact of public credit registry coverages on crash risk. The subsamples are grouped by a proxy of information environment. *IFRS Adoption* is a group of countries that adopts IFRS while *Non-IFRS Adoption* is a group of countries that does not IFRS.
The dependent variable is crash stock measured by *NCSKEW*. *NCSKEW* is a negative conditional skewness of returns; *PUB* is public credit registry coverage (% of adult population); *DTURN* the detrended average monthly stock turnover; *SIGMA* is the standard deviation of firm-specific weekly return over the year; *MEAN* is the average arithmetic mean of firm-specific weekly return over the year; *MV* is the market value of equity; *MTBV* is the natural logarithm of the market value of equity divided by the value of equity; *LEV* is the leverage ratio calculated as total liability to total assets; *ROA* is a return on assets calculated as income before extraordinary items divided by total assets; *CAR_TIER1* is a tier1 capital adequacy ratio; *DEPOSIT* is a ratio of total deposits to total assets; *GDPG* is real GDP growth; *MKTCAP* is the stock market capitalization scaled by GDP; *GDPPC* is the natural logarithm of GDP per capital. Further detail of all variables are presented in Table 4-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.
* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 4-16: Subsample Analysis for the Impact of Public Credit Registry Coverages on Bank Stock Price Crash Risk - grouped by Bank Regulations

	NCSKEW					
Variable	***HIGH CAPITAL_STR***	***LOW CAPITAL_STR***	***HIGH SUPER_POW***	***LOW SUPER_POW***	***HIGH MONITOR***	***LOW MONITOR***
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
PUB	-0.32	-0.632***	-0.418	-0.527**	-0.413**	-0.759***
	(-1.05)	(-4.38)	(-1.11)	(-2.37)	(-2.01)	(-3.05)
DTURN	0.023***	0.009***	0.022***	0.003	0.206	0.001
	(6.35)	(3.29)	(7.40)	(0.42)	(0.88)	(0.13)
SIGMA	2.301***	5.307*	3.264**	2.028	5.030***	1.082
	(6.41)	(1.84)	(2.42)	(1.23)	(6.1)	(0.44)
MEAN	-5.858***	5.726	-5.248***	-2.098	-0.578	-13.291***
	(-4.60)	(0.66)	(-3.61)	(-0.25)	(-0.18)	(-4.06)
MV	0.014**	0.049**	0.031*	0.024	0.066***	-0.03
	(2.79)	(2.09)	(2.04)	(1.32)	(7.05)	(-1.10)
MTBV	0.487	-0.018	0.004	1.881	-0.013	-0.032
	(0.49)	(-1.64)	(0.38)	(1.09)	(-1.03)	(-1.18)
LEV	-0.714	0.595	0.265	-0.911	-0.407	-0.481
	(-1.03)	(0.87)	(0.86)	(-1.50)	(-0.64)	(-0.70)
ROA	-5.091***	-1.783	-4.360***	-3.895***	-4.962***	-2.088
	(-7.49)	(-0.60)	(-3.03)	(-4.17)	(-7.95)	(-0.85)
CAR_TIER1	-0.006	0.004	0.001	-0.007	0.001	-0.013**
	(-1.06)	(0.64)	(0.48)	(-1.35)	(0.26)	(-2.59)
DEPOSIT	-0.033	-0.168	0.026	-0.268	0.251	-0.480**
	(-0.16)	(-0.74)	(0.25)	(-1.16)	(1.2)	(-2.45)
GDPG	-1.261	-0.158	-3.707*	0.48	-0.305	-3.626
	(-0.72)	(-0.13)	(-2.06)	(0.41)	(-0.33)	(-1.39)
MKTCAP	0.019	-0.004	0.049	0.014	-0.099	0.274***
	(0.24)	(-0.06)	(0.54)	(0.16)	(-1.19)	(2.88)
GDPPC	0.090**	0.100***	0.055	0.082***	0.110***	-0.043
	(2.68)	(3.63)	(1.36)	(3.79)	(5.32)	(-0.91)
Constant	-0.948	-2.994***	-1.876*	-0.732	-2.538***	1.324
	(-1.21)	(-3.11)	(-1.89)	(-1.11)	(-2.92)	(1.45)
R-squared	0.079	0.063	0.081	0.064	0.083	0.071
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,048	2,029	4,996	2,081	4,179	2,898

This table presents the regression for the impact of public credit registry coverages on crash risk. The subsamples are grouped by banking regulatory variables. *LOW_CAPITAL_STR* is a dummy variable whose value is equal to one if a country has low capital stringency index and zero for *HIGH_CAPITAL_STR; LOW_SUPER_POW* is a dummy variable whose value is equal to one if a country has low supervisory power index and zero for *HIGH_SUPER_POW; LOW_MONITOR* is a dummy variable whose value is equal to one if a country has low private monitoring index and zero for *HIGH_MONITOR;*

The dependent variable is crash stock measured by *NCSKEW. NCSKEW* is a negative conditional skewness of returns; *PUB* is public credit registry coverage (% of adult population); *DTURN* the detrended average monthly stock turnover; *SIGMA* is the standard deviation of firm-specific weekly return over the year; *MEAN* is the average arithmetic mean of firm-specific weekly return over the year; *MV* is the market value of equity; *MTBV* is the natural logarithm of the market value of equity divided by the value of equity; *LEV* is the leverage ratio calculated as total liability to total assets; *ROA* is a return on assets calculated as income before extraordinary items divided by total assets; *CAR_TIER1* is a tier1 capital adequacy ratio; *DEPOSIT* is a ratio of total deposits to total assets; *GDPG* is real GDP growth; *MKTCAP* is the stock market capitalization scaled by GDP; *GDPPC* is the natural logarithm of GDP per capital. Further detail of all variables are presented in Table 4-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 4-17: Estimation results with Additional Control Variables for the Impact of Public Credit Registry Coverages on Bank Stock Price Crash Risk

Variable	NCSKEW							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PUB	-0.462***	-0.448**	-0.454**	-0.467***	-0.468***	-0.467***	-0.492***	-0.466***
	(-2.72)	(-2.60)	(-2.62)	(-2.69)	(-2.75)	(-2.77)	(-2.90)	(-2.76)
DTURN	0.001*	0.001*	0.001*	0.001*	0.001*	0.001*	0.001*	0.001*
	(1.76)	(1.68)	(1.68)	(1.71)	(1.78)	(1.78)	(1.79)	(1.94)
SIGMA	2.972***	3.027***	3.023***	3.017***	2.955***	2.965***	2.944***	3.055***
	(3.53)	(3.57)	(3.52)	(3.51)	(3.56)	(3.52)	(3.49)	(3.66)
MEAN	-4.005*	-3.963	-3.970	-3.986	-4.032*	-4.013*	-3.955	-3.839*
	(-1.68)	(-1.65)	(-1.65)	(-1.67)	(-1.70)	(-1.68)	(-1.64)	(-1.68)
MV	0.032***	0.032***	0.032***	0.031***	0.031***	0.032***	0.030***	0.031***
	(3.15)	(3.16)	(3.16)	(3.12)	(3.11)	(3.09)	(3.02)	(2.81)
MTBV	-0.011	-0.011	-0.010	-0.012	-0.011	-0.011	-0.009	-0.011
	(-1.13)	(-1.06)	(-1.00)	(-1.20)	(-1.15)	(-1.10)	(-0.89)	(-1.19)
LEV	-0.195	-0.252	-0.255	-0.255	-0.177	-0.181	-0.033	-0.227
	(-0.39)	(-0.50)	(-0.49)	(-0.48)	(-0.37)	(-0.36)	(-0.07)	(-0.46)
ROA	-4.536***	-4.560***	-4.546***	-4.559***	-4.522***	-4.529***	-4.439***	-4.509***
	(-5.70)	(-5.86)	(-5.78)	(-5.92)	(-5.67)	(-5.76)	(-5.50)	(-5.87)
CAR_TIER1	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.002
	(-0.37)	(-0.40)	(-0.40)	(-0.40)	(-0.38)	(-0.37)	(-0.32)	(-0.43)
DEPOSIT	0.034	0.040	0.032	0.032	0.027	0.033	0.016	0.044
	(0.25)	(0.30)	(0.24)	(0.24)	(0.20)	(0.24)	(0.12)	(0.31)
GDPG	-0.635	-0.647	-0.595	-0.676	-0.714	-0.649	-1.069	-0.633
	(-0.53)	(-0.54)	(-0.49)	(-0.58)	(-0.64)	(-0.56)	(-0.99)	(-0.53)
MKTCAP	-0.017	-0.020	-0.028	-0.015	-0.008	-0.013	-0.009	-0.022
	(-0.29)	(-0.37)	(-0.51)	(-0.27)	(-0.15)	(-0.23)	(-0.17)	(-0.40)
GDPPC	0.085***	0.071*	0.068	0.066**	0.098*	0.090**	0.098***	0.086***
	(3.21)	(1.95)	(1.59)	(2.14)	(1.76)	(2.06)	(3.27)	(3.31)
CORRUPTION		0.023						
		(0.61)						
GOV_EFF			0.037					
			(0.59)					
POLITIC				0.033				
				(0.80)				
REG_QUA					-0.031			
					(-0.31)			
RULE_LAW						-0.010		
						(-0.16)		
VOICE_ACC							-0.052	
							(-1.16)	
C_SCORE								-0.165
								(-0.95)
Constant	-1.775***	-1.615***	-1.598**	-1.525**	-1.879***	-1.824***	-1.962***	-0.851
	(-3.28)	(-2.74)	(-2.50)	(-2.24)	(-3.07)	(-2.79)	(-3.42)	(-0.77)
R-squared	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,562	7,562	7,562	7,562	7,562	7,562	7,562	7,562

This table presents the regression for the impact of public credit registry coverages on crash risk with additional control variables. The additional control variables are *CORRUPTION, GOV_EFF, POLITIC, REG_QUA, RULE_LAW, VOICE_ACC* and *C_SCORE.* The dependent variable is crash stock measured by *NCSKEW. NCSKEW* is a negative conditional skewness of returns; *PUB* is public credit registry coverage (% of adult population); *DTURN* the detrended average monthly stock turnover; *SIGMA* is the standard deviation of firm-specific weekly return over the year; *MEAN* is the average arithmetic mean of firm-specific weekly return over the year; *MV* is the market value of equity; *MTBV* is the natural logarithm of the market value of equity divided by the value of equity; *LEV* is the leverage ratio calculated as total liability to total assets; *ROA* is a return on assets calculated as income before extraordinary items divided by total assets; *CAR_TIER1* is a tier1 capital adequacy ratio; *DEPOSIT* is a ratio of total deposits to total assets; GDPG is real GDP growth; *MKTCAP* is the stock market capitalization scaled by GDP; *GDPPC* is the natural logarithm of GDP per capital; *CORRUPTION* is a control of corruption index; *GOV_EFF* is a government effectiveness index; *POLITIC* is a political stability index; *REG_QUA* is a regulatory quality index; *RULE_LAW* is a rule of law index; *VOICE_ACC* is a voice and accountability index; *C_SCORE* is a measure of accounting conservatism. Further detail of all variables are presented in Table 4-1 in

this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.
* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 4-18: Estimation Results with Additional Control Variables for the Interaction Effect of Information Asymmetry and Public Credit Registry Coverages on Bank Stock Price Crash Risk

Variable	*NCSKEW*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PUB	-0.870***	-0.858***	-0.903***	-0.892***	-0.865***	-0.870***	-0.914***	-0.875***
	(-6.91)	(-6.30)	(-7.03)	(-6.65)	(-6.49)	(-6.95)	(-6.99)	(-6.99)
IFRS	-0.052*	-0.047	-0.050*	-0.045	-0.049*	-0.051*	-0.042	-0.051*
	(-1.77)	(-1.57)	(-1.70)	(-1.54)	(-1.68)	(-1.75)	(-1.54)	(-1.77)
IFRS * PUB	0.510*	0.511*	0.564**	0.531*	0.499*	0.509*	0.528*	0.510*
	(1.91)	(1.91)	(2.12)	(2.00)	(1.80)	(1.92)	(1.96)	(1.90)
DTURN	0.001*	0.001*	0.001*	0.001*	0.001*	0.001*	0.001*	0.001**
	(1.84)	(1.80)	(1.77)	(1.84)	(1.88)	(1.83)	(1.88)	(2.03)
SIGMA	2.989***	3.033***	3.046***	3.023***	2.979***	2.989***	2.943***	3.071***
	(3.53)	(3.58)	(3.52)	(3.51)	(3.55)	(3.51)	(3.48)	(3.66)
MEAN	-3.986*	-3.947	-3.938	-3.964	-3.999*	-3.987	-3.933	-3.820
	(-1.68)	(-1.65)	(-1.63)	(-1.66)	(-1.69)	(-1.67)	(-1.63)	(-1.67)
MV	0.030***	0.030***	0.030***	0.029***	0.029***	0.030***	0.028***	0.028**
	(2.87)	(2.89)	(2.89)	(2.86)	(2.87)	(2.86)	(2.82)	(2.57)
MTBV	-0.012	-0.012	-0.011	-0.013	-0.012	-0.012	-0.010	-0.012
	(-1.14)	(-1.12)	(-1.06)	(-1.28)	(-1.14)	(-1.07)	(-1.01)	(-1.18)
LEV	-0.258	-0.305	-0.334	-0.313	-0.247	-0.258	-0.083	-0.289
	(-0.51)	(-0.60)	(-0.63)	(-0.58)	(-0.50)	(-0.49)	(-0.16)	(-0.58)
ROA	-4.532***	-4.559***	-4.552***	-4.567***	-4.527***	-4.532***	-4.447***	-4.506***
	(-5.67)	(-5.81)	(-5.78)	(-5.93)	(-5.66)	(-5.74)	(-5.48)	(-5.83)
CAR_TIER1	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.001	-0.002
	(-0.45)	(-0.47)	(-0.49)	(-0.47)	(-0.45)	(-0.45)	(-0.38)	(-0.51)
DEPOSIT	0.003	0.012	0.002	0.006	0.001	0.003	-0.008	0.013
	(0.02)	(0.08)	(0.01)	(0.05)	(0.01)	(0.02)	(-0.06)	(0.09)
GDPG	-0.616	-0.630	-0.567	-0.665	-0.655	-0.616	-1.062	-0.615
	(-0.52)	(-0.52)	(-0.47)	(-0.57)	(-0.59)	(-0.53)	(-0.97)	(-0.52)
MKTCAP	0.011	0.007	-0.003	0.012	0.014	0.011	0.017	0.005
	(0.18)	(0.11)	(-0.05)	(0.19)	(0.24)	(0.18)	(0.28)	(0.09)
GDPPC	0.081***	0.068*	0.059	0.060*	0.087	0.081*	0.094***	0.082***
	(3.07)	(1.87)	(1.38)	(1.96)	(1.53)	(1.89)	(3.15)	(3.16)
CORRUPTION		0.021						
		(0.55)						
GOV_EFF			0.047					
			(0.78)					
POLITIC				0.035				
				(0.82)				
REG_QUA					-0.015			
					(-0.15)			
RULE_LAW						-0.001		
						(-0.01)		
VOICE_ACC							-0.052	
							(-1.14)	
C_SCORE								-0.165
								(-0.94)
Constant	-1.588***	-1.455**	-1.361**	-1.343*	-1.645**	-1.591**	-1.807***	-0.667
	(-2.72)	(-2.39)	(-2.02)	(-1.92)	(-2.40)	(-2.22)	(-2.86)	(-0.59)
R-squared	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,562	7,562	7,562	7,562	7,562	7,562	7,562	7,562

This table presents the regression for the impact of information asymmetry (proxied by *IFRS*) on the relationship between public credit registry coverages and crash risk with additional control variables. The additional control variables are *CORRUPTION, GOV_EFF, POLITIC, REG_QUA, RULE_LAW, VOICE_ACC* and *C_SCORE.*
The dependent variable is crash stock measured by *NCSKEW. NCSKEW* is a negative conditional skewness of returns; *PUB* is public credit registry coverage (% of adult population); *IFRS* is a dummy variable indicating whether a country adopts IFRS or not; *DTURN* the detrended average monthly stock turnover; *SIGMA* is the standard deviation of firm-specific weekly return over the year; *MEAN* is the average arithmetic mean of firm-specific weekly return over the year; *MV* is the market value of equity;

MTBV is the natural logarithm of the market value of equity divided by the value of equity; *LEV* is the leverage ratio calculated as total liability to total assets; *ROA* is a return on assets calculated as income before extraordinary items divided by total assets; *CAR_TIER1* is a tier1 capital adequacy ratio; *DEPOSIT* is a ratio of total deposits to total assets; GDPG is real GDP growth; *MKTCAP* is the stock market capitalization scaled by GDP; *GDPPC* is the natural logarithm of GDP per capital; *CORRUPTION* is a control of corruption index; *GOV_EFF* is a government effectiveness index; *POLITIC* is a political stability index; *REG_QUA* is a regulatory quality index; *RULE_LAW* is a rule of law index; *VOICE_ACC* is a voice and accountability index; *C_SCORE* is a measure of accounting conservatism. Further detail of all variables are presented in Table 4-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 4-19: Estimation Results with Additional Control Variables for the Interaction Effect of Capital Stringency Regulation and Public Credit Registry Coverages on Bank Stock Price Crash Risk

Variable	*NCSKEW*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PUB	-0.454**	-0.440**	-0.447**	-0.461**	-0.453**	-0.456**	-0.479**	-0.458**
	(-2.53)	(-2.41)	(-2.42)	(-2.52)	(-2.51)	(-2.52)	(-2.65)	(-2.57)
LOW_CAPITAL_STR	0.090*	0.100*	0.096*	0.097*	0.090*	0.089*	0.090*	0.092*
	(1.99)	(1.94)	(1.92)	(1.93)	(1.99)	(1.99)	(1.99)	(1.90)
LOW_CAPITAL_STR * PUB	-3.389***	-3.358***	-3.368***	-3.375***	-3.388***	-3.397***	-3.369***	-3.393***
	(-3.55)	(-3.52)	(-3.50)	(-3.50)	(-3.55)	(-3.56)	(-3.55)	(-3.56)
DTURN	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.002
	(0.14)	(0.12)	(0.11)	(0.13)	(0.14)	(0.14)	(0.17)	(0.35)
SIGMA	3.293***	3.344***	3.344***	3.313***	3.296***	3.290***	3.268***	3.381***
	(3.21)	(3.17)	(3.16)	(3.18)	(3.20)	(3.19)	(3.18)	(3.32)
MEAN	-3.938	-3.893	-3.906	-3.928	-3.935	-3.941	-3.883	-3.763
	(-1.65)	(-1.62)	(-1.62)	(-1.64)	(-1.65)	(-1.65)	(-1.60)	(-1.63)
MV	0.029**	0.030**	0.030**	0.029**	0.029**	0.029**	0.028**	0.028**
	(2.64)	(2.63)	(2.64)	(2.63)	(2.62)	(2.62)	(2.56)	(2.38)
MTBV	0.007	0.007	0.008	0.006	0.007	0.007	0.009	0.006
	(0.60)	(0.62)	(0.68)	(0.55)	(0.60)	(0.56)	(0.79)	(0.58)
LEV	-0.133	-0.183	-0.193	-0.167	-0.136	-0.127	-0.002	-0.164
	(-0.29)	(-0.39)	(-0.39)	(-0.34)	(-0.30)	(-0.27)	(-0.00)	(-0.36)
ROA	-4.630***	-4.669***	-4.651***	-4.656***	-4.632***	-4.627***	-4.550***	-4.604***
	(-5.92)	(-6.16)	(-6.07)	(-6.15)	(-5.98)	(-6.02)	(-5.83)	(-6.08)
CAR_TIER1	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(-0.18)	(-0.18)	(-0.19)	(-0.18)	(-0.17)	(-0.18)	(-0.14)	(-0.22)
DEPOSIT	-0.081	-0.069	-0.082	-0.076	-0.081	-0.081	-0.095	-0.071
	(-0.52)	(-0.44)	(-0.52)	(-0.48)	(-0.52)	(-0.52)	(-0.63)	(-0.44)
GDPG	-0.487	-0.512	-0.447	-0.532	-0.477	-0.493	-0.855	-0.476
	(-0.43)	(-0.44)	(-0.39)	(-0.47)	(-0.44)	(-0.44)	(-0.82)	(-0.42)
MKTCAP	-0.001	-0.007	-0.016	-0.002	-0.002	0.001	0.005	-0.007
	(-0.02)	(-0.13)	(-0.28)	(-0.04)	(-0.03)	(0.01)	(0.09)	(-0.12)
GDPPC	0.071***	0.054	0.051	0.055*	0.069	0.073*	0.082***	0.073***
	(3.05)	(1.61)	(1.29)	(1.85)	(1.26)	(1.80)	(3.07)	(3.18)
CORRUPTION		0.028						
		(0.69)						
GOV_EFF			0.044					
			(0.69)					
POLITIC				0.027				
				(0.59)				
REG_QUA					0.004			
					(0.04)			
RULE_LAW						-0.004		
						(-0.07)		
VOICE_ACC							-0.043	
							(-0.94)	
C_SCORE								-0.163
								(-0.95)
Constant	-1.588**	-1.423**	-1.393**	-1.410**	-1.576**	-1.610**	-1.741***	-0.679
	(-2.66)	(-2.31)	(-2.08)	(-2.10)	(-2.29)	(-2.28)	(-2.77)	(-0.59)
R-squared	0.068	0.068	0.068	0.068	0.068	0.068	0.068	0.069
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,077	7,077	7,077	7,077	7,077	7,077	7,077	7,077

This table presents the regression for the impact of capital regulation on the relationship between public credit registry coverages and crash risk with additional control variables. The additional control variables are *CORRUPTION, GOV_EFF, POLITIC, REG_QUA, RULE_LAW, VOICE_ACC* and *C_SCORE.*
The dependent variable is crash stock measured by *NCSKEW*. *NCSKEW* is a negative conditional skewness of returns; *PUB* is public credit registry coverage (% of adult population); *CAPITAL_STR_LOW* is a dummy variable taking a value of one if the capital stringency index is less than the median value of the sample and zero otherwise; *DTURN* the detrended average monthly stock turnover; *SIGMA* is the standard deviation of firm-specific weekly return over the year; *MEAN* is the average arithmetic mean of firm-specific weekly return over the year; *MV* is the market value of equity; *MTBV* is the natural logarithm of the market value of equity divided by the value of equity; *LEV* is the leverage ratio calculated as total liability to total assets; *ROA* is a return on assets calculated as income before extraordinary items divided by total assets; *CAR_TIER1* is a tier1 capital adequacy ratio; *DEPOSIT* is a ratio of total deposits to total assets; GDPG is real GDP growth; *MKTCAP* is the stock market capitalization scaled by GDP; *GDPPC* is the natural logarithm of GDP per capital; *CORRUPTION* is a control of corruption index; *GOV_EFF* is a government effectiveness index; *POLITIC* is a political stability index; *REG_QUA* is a regulatory quality index; *RULE_LAW* is a rule of law index; *VOICE_ACC* is a voice and accountability index; *C_SCORE* is a measure of accounting conservatism. Further detail of all variables are presented in Table 4-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.
*   indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 4-20: Estimation Results with Additional Control Variables for the Interaction Effect of Supervisory Power and Public Credit Registry Coverages on Bank Stock Price Crash Risk

Variable	NCSKEW							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PUB	-0.436**	-0.430**	-0.432**	-0.441**	-0.437**	-0.448**	-0.460**	-0.440**
	(-2.40)	(-2.39)	(-2.38)	(-2.38)	(-2.40)	(-2.50)	(-2.54)	(-2.44)
LOW_SUPER_POW	0.138	0.142	0.143	0.139	0.137	0.129	0.125	0.139
	(1.17)	(1.26)	(1.24)	(1.18)	(1.17)	(1.13)	(1.10)	(1.21)
LOW_SUPER_POW * PUB	-5.124***	-5.062***	-5.003***	-5.142***	-5.127***	-5.215***	-4.992***	-5.122***
	(-3.69)	(-3.39)	(-3.18)	(-3.71)	(-3.63)	(-3.70)	(-3.72)	(-3.81)
DTURN	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.003
	(0.22)	(0.21)	(0.21)	(0.21)	(0.22)	(0.23)	(0.23)	(0.44)
SIGMA	3.180***	3.195***	3.194***	3.194***	3.178***	3.169***	3.163***	3.265***
	(3.38)	(3.37)	(3.34)	(3.36)	(3.37)	(3.37)	(3.36)	(3.51)
MEAN	-3.967*	-3.953	-3.960	-3.959	-3.970*	-3.974*	-3.918	-3.796
	(-1.68)	(-1.66)	(-1.67)	(-1.67)	(-1.68)	(-1.68)	(-1.64)	(-1.66)
MV	0.028**	0.028**	0.028**	0.028**	0.028**	0.027**	0.027**	0.027**
	(2.57)	(2.55)	(2.55)	(2.56)	(2.55)	(2.53)	(2.52)	(2.30)
MTBV	-0.010	-0.010	-0.009	-0.010	-0.010	-0.011	-0.008	-0.010
	(-0.98)	(-0.96)	(-0.93)	(-1.04)	(-0.96)	(-1.03)	(-0.83)	(-1.04)
LEV	-0.311	-0.331	-0.333	-0.340	-0.308	-0.282	-0.195	-0.342
	(-0.65)	(-0.68)	(-0.66)	(-0.67)	(-0.65)	(-0.57)	(-0.39)	(-0.73)
ROA	-4.578***	-4.592***	-4.585***	-4.598***	-4.577***	-4.565***	-4.512***	-4.552***
	(-5.68)	(-5.82)	(-5.77)	(-5.88)	(-5.72)	(-5.73)	(-5.64)	(-5.83)
CAR_TIER1	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.002	-0.003
	(-0.70)	(-0.70)	(-0.70)	(-0.70)	(-0.70)	(-0.71)	(-0.66)	(-0.76)
DEPOSIT	-0.102	-0.096	-0.100	-0.097	-0.102	-0.106	-0.116	-0.092
	(-0.65)	(-0.63)	(-0.65)	(-0.63)	(-0.67)	(-0.70)	(-0.78)	(-0.57)
GDPG	-0.372	-0.372	-0.345	-0.406	-0.384	-0.418	-0.707	-0.360
	(-0.33)	(-0.33)	(-0.31)	(-0.36)	(-0.35)	(-0.38)	(-0.67)	(-0.32)
MKTCAP	-0.005	-0.006	-0.009	-0.005	-0.004	0.001	0.001	-0.011
	(-0.08)	(-0.11)	(-0.15)	(-0.09)	(-0.07)	(0.02)	(0.01)	(-0.19)
GDPPC	0.084***	0.078**	0.077*	0.072**	0.086	0.094**	0.093***	0.086***
	(3.45)	(2.34)	(1.95)	(2.21)	(1.61)	(2.40)	(3.28)	(3.55)
CORRUPTION		0.010						
		(0.28)						
GOV_EFF			0.016					
			(0.25)					
POLITIC				0.021				
				(0.46)				
REG_QUA					-0.004			
					(-0.04)			
RULE_LAW						-0.021		
						(-0.34)		
VOICE_ACC							-0.036	
							(-0.81)	
C_SCORE								-0.159
								(-0.92)
Constant	-1.500**	-1.440**	-1.431**	-1.357*	-1.513**	-1.596**	-1.628**	-0.610
	(-2.58)	(-2.29)	(-2.09)	(-1.95)	(-2.21)	(-2.23)	(-2.59)	(-0.55)
R-squared	0.068	0.068	0.068	0.068	0.068	0.068	0.068	0.068
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,077	7,077	7,077	7,077	7,077	7,077	7,077	7,077

This table presents the regression for the impact of supervisory power on the relationship between public credit registry coverages and crash risk with additional control variables. The additional control variables are *CORRUPTION, GOV_EFF, POLITIC, REG_QUA, RULE_LAW, VOICE_ACC* and *C_SCORE*.

The dependent variable is crash stock measured by *NCSKEW*. *NCSKEW* is a negative conditional skewness of returns; *PUB* is public credit registry coverage (% of adult population); *SUPER_POW_LOW* is a dummy variable taking a value of one if the supervisory power index is less than the median value of the sample and zero otherwise; *DTURN* the detrended average monthly stock turnover; *SIGMA* is the standard deviation of firm-specific weekly return over the year; *MEAN* is the average arithmetic mean of firm-specific weekly return over the year; *MV* is the market value of equity; *MTBV* is the natural logarithm of the market value of equity divided by the value of equity; *LEV* is the leverage ratio calculated as total liability to total assets; *ROA* is a return on assets calculated as income before extraordinary items divided by total assets; *CAR_TIER1* is a tier1 capital adequacy ratio; *DEPOSIT* is a ratio of total deposits to total assets; GDPG is real GDP growth; *MKTCAP* is the stock market capitalization scaled by GDP; *GDPPC* is the natural logarithm of GDP per capital; *CORRUPTION* is a control of corruption index; *GOV_EFF* is a government effectiveness index; *POLITIC* is a political stability index; *REG_QUA* is a regulatory quality index; *RULE_LAW* is a rule of law index; *VOICE_ACC* is a voice and accountability index; *C_SCORE* is a measure of accounting conservatism. Further detail of all variables are presented in Table 4-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

* indicates significance at the 10% level

** indicates significance at the 5% level

*** indicates significance at the 1% level

Table 4-21: Estimation Results with Additional Control Variables for the Interaction Effect of Market Monitoring and Public Credit Registry Coverages on Bank Stock Price Crash Risk

Variable	*NCSKEW*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PUB	-0.465**	-0.459**	-0.463**	-0.473**	-0.470**	-0.481***	-0.491***	-0.469***
	(-2.63)	(-2.56)	(-2.61)	(-2.63)	(-2.66)	(-2.75)	(-2.77)	(-2.68)
LOW_MONITOR	0.074*	0.078*	0.076*	0.085*	0.074*	0.071*	0.070*	0.070*
	(1.85)	(1.82)	(1.83)	(1.91)	(1.85)	(1.79)	(1.79)	(1.80)
LOW_MONITOR * PUB	-4.146***	-4.068***	-4.051***	-4.255***	-4.216***	-4.352***	-4.198***	-4.134***
	(-8.08)	(-7.76)	(-6.14)	(-7.77)	(-8.02)	(-8.41)	(-8.34)	(-8.19)
DTURN	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.002
	(0.16)	(0.16)	(0.16)	(0.15)	(0.18)	(0.19)	(0.20)	(0.37)
SIGMA	3.319***	3.340***	3.331***	3.353***	3.301***	3.297***	3.291***	3.398***
	(3.32)	(3.30)	(3.27)	(3.30)	(3.31)	(3.30)	(3.29)	(3.44)
MEAN	-3.765	-3.746	-3.759	-3.737	-3.784	-3.778	-3.707	-3.603
	(-1.53)	(-1.51)	(-1.52)	(-1.50)	(-1.53)	(-1.53)	(-1.48)	(-1.51)
MV	0.031***	0.031***	0.031***	0.031***	0.031***	0.030**	0.030**	0.030**
	(2.74)	(2.71)	(2.68)	(2.75)	(2.69)	(2.65)	(2.65)	(2.46)
MTBV	-0.010	-0.010	-0.010	-0.011	-0.011	-0.012	-0.008	-0.011
	(-1.07)	(-1.04)	(-1.02)	(-1.19)	(-1.08)	(-1.15)	(-0.91)	(-1.13)
LEV	-0.228	-0.247	-0.242	-0.273	-0.212	-0.187	-0.090	-0.260
	(-0.47)	(-0.51)	(-0.49)	(-0.53)	(-0.45)	(-0.39)	(-0.19)	(-0.55)
ROA	-4.640***	-4.658***	-4.646***	-4.681***	-4.630***	-4.618***	-4.554***	-4.613***
	(-5.75)	(-5.89)	(-5.84)	(-6.07)	(-5.75)	(-5.76)	(-5.64)	(-5.91)
CAR_TIER1	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.003
	(-0.63)	(-0.63)	(-0.63)	(-0.63)	(-0.63)	(-0.65)	(-0.59)	(-0.69)
DEPOSIT	-0.142	-0.137	-0.142	-0.137	-0.145	-0.145	-0.156	-0.132
	(-0.93)	(-0.93)	(-0.93)	(-0.91)	(-0.96)	(-0.96)	(-1.08)	(-0.84)
GDPG	-0.468	-0.476	-0.456	-0.524	-0.536	-0.513	-0.862	-0.462
	(-0.42)	(-0.43)	(-0.41)	(-0.48)	(-0.50)	(-0.48)	(-0.84)	(-0.41)
MKTCAP	-0.018	-0.021	-0.022	-0.021	-0.013	-0.008	-0.011	-0.023
	(-0.32)	(-0.36)	(-0.36)	(-0.38)	(-0.22)	(-0.13)	(-0.20)	(-0.42)
GDPPC	0.079***	0.072**	0.073*	0.057*	0.089	0.095**	0.091***	0.081***
	(3.48)	(2.04)	(1.80)	(1.85)	(1.64)	(2.42)	(3.40)	(3.60)
CORRUPTION		0.012						
		(0.25)						
GOV_EFF			0.012					
			(0.17)					
POLITIC				0.038				
				(0.77)				
REG_QUA					-0.024			
					(-0.23)			
RULE_LAW						-0.032		
						(-0.50)		
VOICE_ACC							-0.045	
							(-0.99)	
C_SCORE								-0.155
								(-0.91)
Constant	-1.595***	-1.531**	-1.546**	-1.356**	-1.681**	-1.742**	-1.751***	-0.724
	(-2.68)	(-2.50)	(-2.31)	(-2.01)	(-2.54)	(-2.50)	(-2.83)	(-0.66)
R-squared	0.068	0.068	0.068	0.068	0.068	0.068	0.068	0.068
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,077	7,077	7,077	7,077	7,077	7,077	7,077	7,077

This table presents the regression for the impact of market monitoring on the relationship between public credit registry coverages and crash risk with additional control variables. The additional control variables are *CORRUPTION, GOV_EFF, POLITIC, REG_QUA, RULE_LAW, VOICE_ACC* and *C_SCORE.*

The dependent variable is crash stock measured by *NCSKEW. NCSKEW* is a negative conditional skewness of returns; *PUB* is public credit registry coverage (% of adult population); *MONITOR LOW* is a dummy variable taking a value of one if the private monitoring index is less than the median value of the sample and zero otherwise; *DTURN* the detrended average monthly stock turnover; *SIGMA* is the standard deviation of firm-specific weekly return over the year; *MEAN* is the average arithmetic mean of firm-specific weekly return over the year; *MV* is the market value of equity; *MTBV* is the natural logarithm of the market value of equity divided by the value of equity; *LEV* is the leverage ratio calculated as total liability to total assets; *ROA* is a return on assets calculated as income before extraordinary items divided by total assets; *CAR_TIER1* is a tier1 capital adequacy ratio; *DEPOSIT* is a ratio of total deposits to total assets; GDPG is real GDP growth; *MKTCAP* is the stock market capitalization scaled by GDP; *GDPPC* is the natural logarithm of GDP per capital; *CORRUPTION* is a control of corruption index; *GOV_EFF* is a government effectiveness index; *POLITIC* is a political stability index; *REG_QUA* is a regulatory quality index; *RULE_LAW* is a rule of law index; *VOICE_ACC* is a voice and accountability index; *C_SCORE* is a measure of accounting conservatism. Further detail of all variables are presented in Table 4-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 4-22: Non-USA Sample Analysis

Variable	NCSKEW		
	(1)	(2)	(3)
DEPTH	-0.010		
	(-0.26)		
PRIV		0.033	
		(0.28)	
PUB			-0.572***
			(-3.93)
DTURN	0.001*	0.000	0.001*
	(1.79)	(1.65)	(1.74)
SIGMA	4.101*	4.149*	3.848*
	(1.93)	(1.96)	(1.79)
MEAN	4.600	4.464	4.346
	(0.72)	(0.71)	(0.68)
MV	0.036*	0.034*	0.040**
	(1.82)	(1.80)	(2.18)
MTBV	-0.030**	-0.027**	-0.012
	(-2.54)	(-2.46)	(-1.08)
LEV	-0.509	-0.626	-0.643
	(-0.64)	(-0.76)	(-0.96)
ROA	-3.527***	-3.511***	-3.419***
	(-3.99)	(-4.09)	(-3.99)
CAR_TIER1	-0.002	-0.002	-0.003
	(-0.30)	(-0.33)	(-0.58)
DEPOSIT	0.139	0.119	0.024
	(0.71)	(0.66)	(0.14)
GDPG	-0.271	-0.113	-0.200
	(-0.23)	(-0.11)	(-0.20)
MKTCAP	0.023	0.023	0.014
	(0.34)	(0.34)	(0.25)
GDPPC	0.111***	0.107***	0.100***
	(4.31)	(3.57)	(4.26)
Constant	-1.950**	-1.806*	-1.710**
	(-2.33)	(-1.86)	(-2.27)
R-squared	0.0376	0.0377	0.0435
Bank Fixed Effects	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes
Observations	3,135	3,135	3,135

This table presents the regression for the impact of public credit registry coverages on crash risk when the sample excludes banks in the USA. The dependent variable is crash stock measured by *NCSKEW*. *NCSKEW* is a negative conditional skewness of returns; *DEPTH* is depth of credit information sharing index; *PRIV* is private credit bureau coverage (% of adult population); *PUB* is public credit registry coverage (% of adult population); *DTURN* the detrended average monthly stock turnover; *SIGMA* is the standard deviation of firm-specific weekly return over the year; *MEAN* is the average arithmetic mean of firm-specific weekly return over the year; *MV* is the market value of equity; *MTBV* is the natural logarithm of the market value of equity divided by the value of equity; *LEV* is the leverage ratio calculated as total liability to total assets; *ROA* is a return on assets calculated as income before extraordinary items divided by total assets; *CAR_TIER1* is a tier1 capital adequacy ratio; *DEPOSIT* is a ratio of total deposits to total assets; *GDPG* is real GDP growth; *MKTCAP* is the stock market capitalization scaled by GDP; *GDPPC* is the natural logarithm of GDP per capital. Further detail of all variables is presented in Table 4-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 4-23: Non-USA Sample Analysis (Continued)

Variable	NCSKEW		NCSKEW		NCSKEW		NCSKEW	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PUB	-0.574***	-0.802***	-0.599***	-0.570***	-0.585***	-0.553***	-0.612***	-0.602***
	(-3.86)	(-5.53)	(-4.19)	(-3.85)	(-3.95)	(-3.68)	(-4.22)	(-4.11)
IFRS	-0.030*	-0.049						
	(-2.51)	(-0.70)						
IFRS * PUB		0.287***						
		-2.16						
LOW_CAPITAL_STR			0.168*	-0.051				
			(1.95)	(-0.26)				
LOW_CAPITAL_STR * PUB				-2.935***				
				(-2.80)				
LOW_SUPER_POW					0.030	0.142		
					(0.25)	(1.26)		
LOW_SUPER_POW * PUB						-4.615***		
						(-3.04)		
LOW_MONITOR							0.158**	-0.050
							(2.04)	(-0.25)
LOW_MONITOR * PUB								-2.852***
								(-2.28)
DTURN	0.001	0.001	0.004	0.004	0.004	0.005	0.003	0.004
	(1.17)	(1.09)	(0.54)	(0.51)	(0.55)	(0.69)	(0.44)	(0.49)
SIGMA	3.877*	3.811*	4.615**	4.698**	4.555**	4.157*	4.783**	4.629**
	(1.78)	(1.76)	(2.08)	(2.13)	(2.06)	(1.80)	(2.18)	(2.05)
MEAN	4.342	4.379	3.959	4.009	4.040	4.413	3.922	4.495
	(0.68)	(0.68)	(0.53)	(0.54)	(0.54)	(0.58)	(0.52)	(0.59)
MV	0.039**	0.038**	0.040**	0.039*	0.039*	0.038*	0.041**	0.042**
	(2.14)	(2.06)	(2.01)	(1.99)	(1.94)	(1.89)	(2.15)	(2.19)
MTBV	-0.011	-0.012	-0.008	0.001	-0.012	-0.013	-0.015	-0.014
	(-0.92)	(-1.03)	(-0.70)	(0.05)	(-1.08)	(-1.13)	(-1.35)	(-1.23)
LEV	-0.651	-0.666	-0.435	-0.406	-0.525	-0.606	-0.532	-0.605
	(-0.97)	(-0.99)	(-0.68)	(-0.63)	(-0.82)	(-0.94)	(-0.83)	(-0.95)
ROA	-3.393***	-3.416***	-3.565***	-3.609***	-3.560***	-3.536***	-3.569***	-3.571***
	(-3.96)	(-3.99)	(-4.34)	(-4.40)	(-4.31)	(-4.33)	(-4.29)	(-4.23)
CAR_TIER1	-0.003	-0.003	-0.003	-0.002	-0.004	-0.005	-0.004	-0.005
	(-0.59)	(-0.61)	(-0.42)	(-0.32)	(-0.62)	(-0.78)	(-0.76)	(-0.82)
DEPOSIT	-0.011	-0.026	-0.164	-0.154	-0.162	-0.192	-0.182	-0.204
	(-0.06)	(-0.14)	(-0.74)	(-0.69)	(-0.75)	(-0.89)	(-0.84)	(-0.94)
GDPG	-0.143	-0.127	0.257	0.282	0.311	0.470	0.306	0.246
	(-0.14)	(-0.12)	(0.26)	(0.28)	(0.30)	(0.45)	(0.32)	(0.25)
MKTCAP	0.013	0.026	0.017	0.006	0.025	-0.005	0.017	0.003
	(0.24)	(0.45)	(0.30)	(0.10)	(0.45)	(-0.08)	(0.33)	(0.05)
GDPPC	0.098***	0.095***	0.089***	0.087***	0.094***	0.096***	0.088***	0.091***
	(4.09)	(3.93)	(4.33)	(4.33)	(4.23)	(4.29)	(3.86)	(4.09)
Constant	-1.626**	-1.539*	-1.695*	-1.724**	-1.669*	-1.529*	-1.588*	-1.536*
	(-2.02)	(-1.87)	(-1.99)	(-2.01)	(-1.99)	(-1.78)	(-1.88)	(-1.82)
R-squared	0.0433	0.0432	0.0507	0.0519	0.0499	0.0520	0.0509	0.0516
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,135	3,135	2,650	2,650	2,650	2,650	2,650	2,650

This table presents the regression for the impact of public credit registry coverages on crash risk when the sample excludes banks in the USA. The dependent variable is crash stock measured by *NCSKEW*. *NCSKEW* is a negative conditional skewness of returns; *PUB* is public credit registry coverage (% of adult population); IFRS is a dummy variable indicating whether a country adopts IFRS or not; *LOW_CAPITAL_STR* is a dummy variable whose value is equal to one if a country has low capital stringency index and zero otherwise; *LOW_SUPER_POW* is a dummy variable whose value is equal to one if a country has low supervisory power index and zero otherwise; *LOW_MONITOR* is a dummy variable whose value is equal to one if a country has low private monitoring index and zero otherwise; *DTURN* the detrended average monthly stock turnover; *SIGMA* is the standard deviation of firm-specific weekly return over the year; *MEAN* is the average arithmetic mean of firm-specific weekly return over the year; *MV* is the market value of equity; *MTBV* is the natural logarithm of the market value of equity divided by the value of equity; *LEV* is the leverage ratio calculated as total liability to total assets; *ROA* is a return on assets calculated as income before extraordinary items divided by total assets; *CAR_TIER1* is a tier1 capital adequacy ratio; *DEPOSIT* is a ratio of total deposits to total assets; *GDPG* is real GDP growth; *MKTCAP* is the stock market capitalization scaled by GDP; *GDPPC* is the natural logarithm of GDP per capital. Further detail of all variables is presented in Table 4-1 in this chapter. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 4-24: IV Approach for the Impact of Public Credit Registry Coverages on Bank Risk Price Crash Risk

Variable	*NCSKEW*	
	IV 2nd-Stage (1)	**IV 1st-Stage (2)**
PUB	-1.068***	
	(-2.61)	
DTURN	0.001	0.000
	(0.41)	(0.32)
SIGMA	2.752***	-0.169***
	(3.95)	(-3.97)
MEAN	-5.161***	-0.071
	(-2.65)	(-0.48)
MV	0.034***	0.008***
	(4.25)	(10.38)
MTBV	0.027	0.008**
	(0.93)	(2.56)
LEV	0.086	0.277***
	(0.17)	(5.08)
ROA	-4.985***	-0.247***
	(-4.40)	(-2.78)
CAR_TIER1	-0.003	-0.000
	(-0.90)	(-1.37)
DEPOSIT	-0.179	-0.087***
	(-1.59)	(-7.97)
GDPG	-1.019*	-0.162***
	(-1.75)	(-2.66)
MKTCAP	0.117***	-0.034***
	(3.08)	(-7.14)
GDPPC	0.053***	-0.015***
	(3.09)	(-6.34)
LEGALORIGIN		0.140***
		(21.25)
ETHNIC_FRAC		-0.049***
		(-5.07)
LATITUDE		-0.374***
		(-14.58)
Constant	-1.370**	0.086
	(-2.46)	(1.28)
R-squared	0.028	0.270
First Stage F-test	189.8	
Second Stage F-test	16.53	
Hansen J-Test	4.109	
Hansen J P-Value	0.128	
Observations	7,236	7,236

This table presents the instrumental variable regression for the impact of public credit registry coverages on crash risk. The instruments are legal origins, ethnic fractionalization, and latitude. The 2nd-stage regression is reported in the odd column, while the 1st-stage regression is reported in the even column.

The dependent variable is crash stock measured by *NCSKEW*. *NCSKEW* is a negative conditional skewness of returns. *PUB* is public credit registry coverage (% of adult population); *DTURN* the detrended average monthly stock turnover; *SIGMA* is the standard deviation of firm-specific weekly return over the year; *MEAN* is the average arithmetic mean of firm-specific weekly return over the year; *MV* is the market value of equity; *MTBV* is the natural logarithm of the market value of equity divided by the value of equity; *LEV* is the leverage ratio calculated as total liability to total assets; *ROA* is a return on assets calculated as income before extraordinary items divided by total assets; *CAR_TIER1* is a tier1 capital adequacy ratio; *DEPOSIT* is a ratio of total deposits to total assets; *GDPG* is real GDP growth; *MKTCAP* is the stock market capitalization scaled by GDP; *GDPPC* is the natural logarithm of GDP per capital; *LEGALORIGIN* is dummy variable whose value is equal to one if a country has English legal origin and otherwise zero; *ETHNIC_FRAC* is an ethnic fractionalization which captures the ethnic diversity in a country; *LATITUDE* is a latitude which measures the geographical latitude of a country. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the country-level are applied in all estimations.

* indicates significance at the 10% level

** indicates significance at the 5% level

*** indicates significance at the 1% level

Table 4-25: IV Approach for the Interaction Effect of Information Asymmetry and Public Credit Registry Coverages on Bank Risk Price Crash Risk

Variable	*NCSKEW*			
	IFRS		Non-IFRS	
	IV 2nd-Stage	IV 1st-Stage	IV 2nd-Stage	IV 1st-Stage
	(1)	(2)	(3)	(4)
PUB	-0.656		-1.202*	
	(-1.24)		(-1.65)	
DTURN	0.027	0.001*	0.000	0.000
	(1.29)	(1.65)	(0.22)	(1.17)
SIGMA	2.852***	-0.085**	1.444	0.408
	(3.86)	(-2.08)	(0.46)	(1.49)
MEAN	-5.629***	-0.106	19.343**	1.689**
	(-2.83)	(-0.72)	(2.52)	(2.31)
MV	0.024***	0.006***	0.049*	0.010***
	(2.62)	(7.68)	(1.72)	(3.48)
MTBV	0.022	0.010***	3.409	-0.357***
	(0.71)	(2.91)	(1.59)	(-2.82)
LEV	-0.446	0.192***	2.889**	-0.083
	(-0.84)	(3.48)	(2.26)	(-0.57)
ROA	-5.208***	-0.078	3.764	-1.856***
	(-4.48)	(-1.15)	(0.85)	(-3.83)
CAR_TIER1	-0.006	-0.001**	0.017*	0.002**
	(-1.45)	(-2.17)	(1.75)	(2.37)
DEPOSIT	-0.272**	-0.128***	0.544	0.300***
	(-2.05)	(-9.14)	(1.46)	(6.78)
GDPG	-1.050	-0.096	-1.071	-0.271**
	(-1.51)	(-1.40)	(-0.99)	(-2.48)
MKTCAP	0.164***	-0.051***	0.230	0.093***
	(3.32)	(-11.77)	(1.30)	(4.17)
GDPPC	0.051***	-0.011***	-0.028	-0.026***
	(2.74)	(-5.05)	(-0.35)	(-3.12)
LEGALORIGIN		0.165***		0.098***
		(13.53)		(4.71)
ETHNIC_FRAC		0.012		0.092***
		(0.62)		(2.76)
LATITUDE		-0.251***		-0.773***
		(-9.67)		(-10.93)
Constant	-0.652	0.073	-4.332***	0.326**
	(-1.02)	(0.98)	(-3.15)	(2.55)
R-squared	0.030	0.268	0.079	0.649
First Stage F-test	113.7		83.36	
Second Stage F-test	16.21		3.650	
Hansen J-Test	3.086		1.568	
Hansen J P-Value	0.214		0.456	
Observations	6,440	6,440	796	796

This table presents the instrumental variable regression for the impact of information asymmetry (proxied by *IFRS*) on the relationship between public credit registry coverages and crash risk. The instruments are legal origins, ethnic fractionalization, and latitude. *IFRS Adoption* is a group of countries that adopts IFRS while *Non-IFRS Adoption* is a group of countries that does not IFRS*;* The 2nd-stage regressions are reported in the odd columns, while the 1st-stage regressions are reported in the even columns.
The dependent variable is crash stock measured by *NCSKEW*. *NCSKEW* is a negative conditional skewness of returns. *PUB* is public credit registry coverage (% of adult population); *DTURN* the detrended average monthly stock turnover; *SIGMA* is the standard deviation of firm-specific weekly return over the year; *MEAN* is the average arithmetic mean of firm-specific weekly return over the year; *MV* is the market value of equity; *MTBV* is the natural logarithm of the market value of equity divided by the value of equity; *LEV* is the leverage ratio calculated as total liability to total assets; *ROA* is a return on assets calculated as income before extraordinary items divided by total assets; *CAR_TIER1* is a tier1 capital adequacy ratio; *DEPOSIT* is a ratio of total deposits to total assets; *GDPG* is real GDP growth; *MKTCAP* is the stock market capitalization scaled by GDP; *GDPPC* is the natural logarithm of GDP per capital; *LEGALORIGIN* is dummy variable whose value is equal to one if a country has English legal origin and otherwise zero; *ETHNIC_FRAC* is an ethnic fractionalization which captures the ethnic diversity in a country; *LATITUDE* is a latitude which measures the geographical latitude of a country. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.
* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 4-26: IV Approach for the Interaction Effect of Capital Stringency Regulation and Public Credit Registry Coverages on Bank Risk Price Crash Risk

Variable	*NCSKEW* HIGH Capital Stringency index IV 2nd-Stage (1)	IV 1st-Stage (2)	LOW Capital Stringency index IV 2nd-Stage (3)	IV 1st-Stage (4)
PUB	0.119		-1.136***	
	(0.23)		(-2.88)	
DTURN	0.028	0.001	0.013***	0.000
	(1.20)	(1.09)	(4.27)	(0.00)
SIGMA	2.717***	-0.049	4.107**	0.247
	(3.27)	(-1.40)	(2.08)	(1.21)
MEAN	-5.432**	-0.140	2.065	-0.307
	(-2.50)	(-1.60)	(0.36)	(-0.42)
MV	0.010	0.004***	0.059***	0.014***
	(1.03)	(4.87)	(3.48)	(8.48)
MTBV	2.185	-0.306***	0.015	0.002
	(1.21)	(-3.29)	(0.52)	(0.54)
LEV	-1.212*	0.134***	0.685	0.050
	(-1.87)	(2.89)	(0.75)	(0.41)
ROA	-5.287***	-0.007	-4.838*	-1.095***
	(-4.19)	(-0.14)	(-1.79)	(-2.59)
CAR_TIER1	-0.013**	-0.000	0.010	-0.001*
	(-2.49)	(-1.22)	(1.58)	(-1.66)
DEPOSIT	-0.148	-0.081***	-0.188	-0.017
	(-0.83)	(-4.65)	(-1.10)	(-0.97)
GDPG	-1.982**	-0.081	0.765	0.087
	(-2.04)	(-1.06)	(0.76)	(0.56)
MKTCAP	0.255***	-0.003	0.103*	-0.034***
	(3.23)	(-0.36)	(1.92)	(-4.58)
GDPPC	0.040	-0.029***	0.106***	0.016***
	(0.59)	(-4.67)	(4.37)	(3.40)
LEGALORIGIN		0.248***		0.173***
		(11.31)		(19.65)
ETHNIC_FRAC		-0.316***		0.068***
		(-7.71)		(3.82)
LATITUDE		0.012		-0.484***
		(0.47)		(-15.04)
Constant	0.294	0.185**	-3.157***	-0.167
	(0.28)	(2.02)	(-3.32)	(-1.40)
R-squared	0.026	0.375	0.046	0.287
First Stage F-test	77.45		215.6	
Second Stage F-test	11.91		8.341	
Hansen J-Test	0.0218		0.844	
Hansen J P-Value	0.989		0.656	
Observations	4,933	4,933	1,830	1,830

This table presents the instrumental variable regression for the impact of capital regulation on the relationship between public credit registry coverages and crash risk. The instruments are legal origins, ethnic fractionalization, and latitude. *CAPITAL_STR* is a capital stringency index: For each column, *HIGH* signifies the above-median group of *CAPITAL_STR,* while *LOW* signifies the below-median group of *CAPITAL_STR.* The 2nd-stage regressions are reported in the odd columns, while the 1st-stage regressions are reported in the even columns. The dependent variable is crash stock measured by *NCSKEW. NCSKEW* is a negative conditional skewness of returns. *PUB* is public credit registry coverage (% of adult population); *DTURN* the detrended average monthly stock turnover; *SIGMA* is the standard deviation of firm-specific weekly return over the year; *MEAN* is the average arithmetic mean of firm-specific weekly return over the year; *MV* is the market value of equity; *MTBV* is the natural logarithm of the market value of equity divided by the value of equity; *LEV* is the leverage ratio calculated as total liability to total assets; *ROA* is a return on assets calculated as income before extraordinary items divided by total assets; *CAR_TIER1* is a tier1 capital adequacy ratio; *DEPOSIT* is a ratio of total deposits to total assets; *GDPG* is real GDP growth; *MKTCAP* is the stock market capitalization scaled by GDP; *GDPPC* is the natural logarithm of GDP per capital; *LEGALORIGIN* is dummy variable whose value is equal to one if a country has English legal origin and otherwise zero; *ETHNIC_FRAC* is an ethnic fractionalization which captures the ethnic diversity in a country; *LATITUDE* is a latitude which measures the geographical latitude of a country. Time dummy variables are added into all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

* indicates significance at the 10% level

** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 4-27: IV Approach for the Interaction Effect of Supervisory Power and Public Credit Registry Coverages on Bank Risk Price Crash Risk

	NCSKEW			
Variable	**HIGH Supervisory Power index**		**LOW Supervisory Power index**	
	IV 2nd-Stage	**IV 1st-Stage**	**IV 2nd-Stage**	**IV 1st-Stage**
	(1)	**(2)**	**(3)**	**(4)**
PUB	-0.654		-1.126*	
	(-0.90)		(-1.79)	
DTURN	0.032	0.001	0.013***	-0.000
	(1.30)	(1.53)	(2.84)	(-0.09)
SIGMA	3.410***	-0.106***	-0.005	-0.349*
	(3.99)	(-2.88)	(-0.00)	(-1.79)
MEAN	-5.468**	-0.059	-0.477	-0.629
	(-2.52)	(-0.55)	(-0.09)	(-0.93)
MV	0.027**	0.002***	0.023	0.012***
	(2.52)	(3.63)	(1.45)	(6.69)
MTBV	0.022	0.008**	1.447	-0.658***
	(0.71)	(2.50)	(0.97)	(-2.65)
LEV	0.008	0.135***	-0.302	-0.057
	(0.01)	(2.74)	(-0.27)	(-0.47)
ROA	-4.746***	-0.113	-5.828***	-0.508**
	(-3.38)	(-1.42)	(-2.66)	(-2.07)
CAR_TIER1	-0.006	-0.000	-0.001	-0.003**
	(-1.08)	(-1.45)	(-0.08)	(-2.47)
DEPOSIT	-0.343*	-0.085***	-0.261	-0.106***
	(-1.81)	(-7.36)	(-1.41)	(-5.57)
GDPG	-1.265	0.211***	-0.460	-0.280**
	(-1.21)	(3.07)	(-0.47)	(-2.10)
MKTCAP	0.161*	-0.062***	0.208***	-0.005
	(1.74)	(-8.86)	(3.58)	(-0.55)
GDPPC	0.053	-0.010**	0.067***	-0.001
	(1.37)	(-2.15)	(2.79)	(-0.23)
LEGALORIGIN		0.190***		0.137***
		(16.55)		(12.43)
ETHNIC_FRAC		-0.165***		0.066***
		(-5.38)		(3.14)
LATITUDE		-0.439***		-0.260***
		(-10.14)		(-6.49)
Constant	-1.127	0.356***	-0.893	0.082
	(-1.32)	(5.78)	(-0.83)	(0.61)
R-squared	0.032	0.464	0.034	0.177
First Stage F-test	242.3		69.74	
Second Stage F-test	13.56		5.649	
Hansen J-Test	4.467		0.409	
Hansen J P-Value	0.107		0.523	
Observations	4,938	4,938	1,825	1,825

This table presents the instrumental variable regression for the impact of supervisory power on the relationship between public credit registry coverages and crash risk. The instruments are legal origins, ethnic fractionalization, and latitude. *SUPER_POW* is a supervisory power index: For each column, *HIGH* signifies the above-median group of *SUPER_POW,* while *LOW* signifies the below-median group of *SUPER_POW.* The 2nd-stage regressions are reported in the odd columns, while the 1st-stage regressions are reported in the even columns. The dependent variable is crash stock measured by *NCSKEW. NCSKEW* is a negative conditional skewness of returns. *PUB* is public credit registry coverage (% of adult population); *DTURN* the detrended average monthly stock turnover; *SIGMA* is the standard deviation of firm-specific weekly return over the year; *MEAN* is the average arithmetic mean of firm-specific weekly return over the year; *MV* is the market value of equity; *MTBV* is the natural logarithm of the market value of equity divided by the value of equity; *LEV* is the leverage ratio calculated as total liability to total assets; *ROA* is a return on assets calculated as income before extraordinary items divided by total assets; *CAR_TIER1* is a

tier1 capital adequacy ratio; *DEPOSIT* is a ratio of total deposits to total assets; *GDPG* is real GDP growth; *MKTCAP* is the stock market capitalization scaled by GDP; *GDPPC* is the natural logarithm of GDP per capital; *LEGALORIGIN* is dummy variable whose value is equal to one if a country has English legal origin and otherwise zero; *ETHNIC_FRAC* is an ethnic fractionalization which captures the ethnic diversity in a country; *LATITUDE* is a latitude which measures the geographical latitude of a country. Time dummy variables are added into all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.
* indicates significance at the 10% level
** indicates significance at the 5% level
*** indicates significance at the 1% level

Table 4-28: IV Approach for the Interaction Effect of Market Monitoring and Public Credit Registry Coverages on Bank Risk Price Crash Risk

	NCSKEW			
Variable	**HIGH Private Monitoring index**		**LOW Private Monitoring index**	
	IV 2nd-Stage	**IV 1st-Stage**	**IV 2nd-Stage**	**IV 1st-Stage**
	(1)	**(2)**	**(3)**	**(4)**
PUB	-0.421		-1.793**	
	(-0.94)		(-2.20)	
DTURN	0.160	-0.023	0.004	-0.000
	(0.75)	(-1.41)	(0.45)	(-0.24)
SIGMA	5.716***	-0.146***	0.008	-0.312***
	(6.63)	(-2.59)	(0.00)	(-2.60)
MEAN	0.015	-0.306*	-16.126***	0.344
	(0.01)	(-1.75)	(-4.07)	(1.21)
MV	0.062***	0.007***	-0.006	0.007***
	(5.73)	(6.94)	(-0.43)	(6.83)
MTBV	-0.007	0.007**	0.023	-0.010
	(-0.23)	(2.19)	(0.40)	(-0.90)
LEV	0.321	0.300***	-0.682	0.143**
	(0.52)	(3.90)	(-0.73)	(2.47)
ROA	-5.056***	-0.065	-5.998*	-1.105***
	(-4.16)	(-0.80)	(-1.80)	(-4.06)
CAR_TIER1	0.003	-0.001**	-0.014*	-0.001**
	(0.59)	(-2.31)	(-1.88)	(-2.51)
DEPOSIT	0.064	-0.187***	-0.673***	-0.040***
	(0.43)	(-8.78)	(-3.11)	(-2.97)
GDPG	0.975	0.055	-10.291***	-0.818***
	(1.29)	(0.73)	(-5.93)	(-2.96)
MKTCAP	-0.108*	-0.038***	0.484***	0.034***
	(-1.76)	(-5.05)	(6.89)	(3.35)
GDPPC	0.126***	-0.009***	-0.174***	-0.048***
	(6.25)	(-3.29)	(-3.96)	(-6.77)
LEGALORIGIN		0.203***		0.160***
		(12.54)		(13.35)
ETHNIC_FRAC		0.026		-0.114***
		(1.04)		(-7.18)
LATITUDE		-0.403***		-0.250***
		(-11.72)		(-7.83)
Constant	-3.146***	0.036	2.918**	0.410***
	(-4.43)	(0.39)	(2.54)	(5.00)
R-squared	0.054	0.307	0.030	0.268
First Stage F-test	167.8		72.40	
Second Stage F-test	17.39		8.700	
Hansen J-Test	4.233		4.629	
Hansen J P-Value	0.120		0.0988	
Observations	3,940	3,940	2,823	2,823

This table presents the instrumental variable regression for the impact of market monitoring on the relationship between public credit registry coverages and crash risk. The instruments are legal origins, ethnic fractionalization, and latitude. For each column, *HIGH* signifies the above-median group of *MONITOR,* while *LOW* signifies the below-median group of *MONITOR*. The 2nd-stage regressions are reported in the odd columns, while the 1st-stage regressions are reported in the even columns. The dependent variable is crash stock measured by *NCSKEW*. *NCSKEW* is a negative conditional skewness of returns. *PUB* is public credit registry coverage (% of adult population); *MONITOR* is a private monitoring index; *DTURN* the detrended average monthly stock turnover; *SIGMA* is the standard deviation of firm-specific weekly return over the year; *MEAN* is the average arithmetic mean of firm-specific weekly return over the year; *MV* is the market value of equity; *MTBV* is the natural logarithm of the market value of equity divided by the value of equity; *LEV* is the leverage ratio calculated as total liability to total assets; *ROA* is a return on assets calculated as income before extraordinary items divided by total assets; *CAR_TIER1* is a tier1 capital adequacy ratio; *DEPOSIT* is a ratio of total deposits to total assets; *GDPG* is real GDP growth; *MKTCAP* is the stock market capitalization scaled by GDP; *GDPPC* is the natural logarithm of GDP per capital; *LEGALORIGIN* is dummy variable whose value is equal to one if a country has English legal origin and otherwise zero; *ETHNIC_FRAC* is an ethnic fractionalization which captures the ethnic diversity in a country; *LATITUDE* is a latitude which measures the geographical latitude of a country. Time dummy variables are added into all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

* indicates significance at the 10% level

** indicates significance at the 5% level

*** indicates significance at the 1% level

Table 4-29: Additional Tests – The Impact of Public Credit Registry Coverages on Bank Stock Price Crash Risk: The Role of Other Aspects of Banking Regulations

Variable	NCSKEW			
	(1)	(2)	(3)	(4)
PUB	-0.430**	1.041**	-0.464**	-0.563***
	(-2.50)	-2.55	(-2.59)	(-3.18)
DEPOSIT_INS	-0.114**	-0.08		
	(-2.24)	(-1.47)		
DEPOSIT_INS * PUB		-1.529***		
		(-3.69)		
LOW_ACTIVITY_RES			-0.068	-0.102
			(-1.64)	(-1.47)
LOW_ACTIVITY_RES * PUB				0.681
				(1.20)
DTURN	0.001	0.001	0.001	0.001
	(1.34)	(1.39)	(0.13)	(0.13)
SIGMA	3.122***	3.053***	3.407***	3.524***
	-3.64	-3.61	(3.41)	(3.28)
MEAN	-3.848	-3.768	-3.943*	-3.862
	(-1.58)	(-1.51)	(-1.69)	(-1.66)
MV	0.026**	0.026**	0.029***	0.029***
	-2.59	-2.58	(2.68)	(2.67)
MTBV	-0.005	-0.001	-0.003	-0.017
	(-0.48)	(-0.10)	(-0.28)	(-1.24)
LEV	-0.311	-0.295	-0.313	-0.319
	(-0.66)	(-0.63)	(-0.69)	(-0.70)
ROA	-4.487***	-4.473***	-4.522***	-4.585***
	(-5.76)	(-5.72)	(-5.56)	(-5.65)
CAR_TIER1	-0.002	-0.002	-0.002	-0.002
	(-0.50)	(-0.48)	(-0.52)	(-0.57)
DEPOSIT	-0.031	-0.032	-0.063	-0.051
	(-0.22)	(-0.23)	(-0.41)	(-0.33)
GDPG	-0.957	-1.432	-0.501	-0.661
	(-0.94)	(-1.34)	(-0.45)	(-0.59)
MKTCAP	0.01	0.017	0.027	0.053
	-0.18	-0.33	(0.49)	(0.78)
GDPPC	0.079***	0.075***	0.086***	0.088***
	-3.2	-2.96	(3.64)	(3.58)
Constant	-1.368**	-1.349**	-1.611***	-1.663***
	(-2.43)	(-2.38)	(-2.78)	(-2.80)
R-squared	0.063	0.064	0.067	0.068
Bank Fixed Effects	Yes	Yes	Yes	Yes
Time Dummy	Yes	Yes	Yes	Yes
Observations	7,562	7,562	7,077	7,077

This table presents the regression for the impact of other regulations on the relationship between public credit registry coverages and crash risk. The other bank regulations consists of a deposit insurance and activity restrictions. The dependent variable is crash stock measured by *NCSKEW*. *NCSKEW* is a negative conditional skewness of returns. *PUB* is public credit registry coverage (% of adult population); *DEPOSIT_INS* is a dummy whose value is equal to one when there exist deposit insurance regime in the country; *LOW_ACTIVITY_RES* is a dummy variable whose value is equal to one when an activity restriction index is low; *DTURN* the detrended average monthly stock turnover; *SIGMA* is the standard deviation of firm-specific weekly return over the year; *MEAN* is the average arithmetic mean of firm-specific weekly return over the year; *MV* is the market value of equity; *MTBV* is the natural logarithm of the market value of equity divided by the value of equity; *LEV* is the leverage ratio calculated as total liability to total assets; *ROA* is a return on assets calculated as income before extraordinary items divided by total assets; *CAR_TIER1* is a tier1 capital adequacy ratio; *DEPOSIT* is a ratio of total deposits to total assets; *GDPG* is real GDP growth; *MKTCAP* is the stock market capitalization scaled by GDP; *GDPPC* is the natural logarithm of GDP per capital. Time dummy variables are included in all regressions. Heteroskedasticity-robust standard errors clustering at the bank-level are applied in all estimations.

*   indicates significance at the 10% level
**   indicates significance at the 5% level
*** indicates significance at the 1% level

Chapter 5: Conclusion

5.1 Summary of Findings

This thesis provides an analysis of the economic consequences of information sharing among banks about their borrowers' information. By using a sample of banks around the globe during the period of 2005 to 2013, we attempt to address the impact of credit information sharing on bank lending, bank risk, and bank-specific stock price crash. We rely on the Bankscope database for bank-level data and the World Bank's Doing Business database for measures of credit information sharing in each country. In addition, we supplement with several other databases, consisting of Datastream, IFRS Foundation website, Deloitte, the World Bank's World Development Indicators database (WDI), the World Bank's Global Financial Development database (GFDD), and the World Bank's Banking and Supervision Survey database.

In chapter 2, our objectives are to investigate the impact of credit information sharing on bank lending and how, and to what extent, information asymmetry and the creditor protection affect it. Investigating the sample of 16,009 banks in 113 countries during 2005 to 2013, we find that credit information sharing promotes bank lending. The result suggests that banks in countries with more credit information sharing tend to extend more loans than those in countries with less credit information sharing. This finding is line with the theoretical literature predicting that credit information sharing facilitates bank lending decision. With more information sharing, banks are more willing to lend as the asymmetric information between banks and borrowers are less problematic.

When banks share borrower information with each other, the asymmetric information between banks and borrowers is less problematic due to several reasons. Firstly, information sharing improves the knowledge of loan applicants' characteristics, such that banks can differentiate between risky and safe borrowers. Secondly, when borrower information is shared among banks, borrowers are not held up to one bank which can charge higher interest rate due to its information monopoly. Thirdly, knowing that banks will share among each other their borrowers' default records, borrowers need to be more disciplined and exert more effort to repay. Lastly, over-borrowing is less likely as banks share information about borrowers' indebtedness. Thus, banks are more confident in lending and more likely to lend with more credit information sharing.

Furthermore, we investigate the impact of information environment on the relationship between credit information sharing and bank lending. When the information environment is more transparent, borrower information should be abundantly available and accessible to the public, such that the asymmetric information between banks and borrowers is less severe. According to our results, we find that the impact of credit information sharing on bank lending is less pronounced in countries with mandatory IFRS adoption and greater extent of business disclosure. These findings suggest that credit information sharing has a weaker impact on bank lending when the information environment is more transparent.

We also study the impact of creditor protection on the relationship between credit information sharing and bank lending. When borrowers default, stronger creditor protection allows banks to grab collaterals, force repayments, or even gain control of the debtor. In this regard, banks are encouraged to take more risks by extending loans to a broader and potentially riskier set of borrowers, regardless of the asymmetric information between banks and borrowers. According to the empirical results, we find that credit information sharing only affects bank lending through its interaction with credit rights. This finding shows that credit information sharing reduces bank lending in countries with well-protected creditors, while it has no notable effect on bank lending in countries with low creditor protection. There are two implications of this finding. Firstly, we can infer that credit information sharing reduces an increase in lending from stronger creditor protection. Secondly, credit information sharing is complementary to creditor rights, such that some degree of creditor protection is required to guarantee the effect of information sharing on lending.

In chapter 3, our objectives are to examine the impact of credit information sharing on bank risk and how, and to what extent, information asymmetry and banking competition affect it. Studying the sample of 15,558 banks in 105 countries during 2005 to 2013, we discover that credit information sharing has a negative impact on bank risk. This finding suggests that banks in countries with more credit information sharing tend to be less risky. We can infer that, while credit information sharing encourages banks to extend more loans (Chapter 2), it does not necessarily lead to riskier lending. The results in chapter 3 suggest that credit information sharing induces banks to lend safely, fostering bank stability.

The negative association between credit information sharing and bank risk is consistent with theoretical literature predicting that credit information sharing contributes to lower bank risk. Firstly, theory suggests that credit information sharing reduces adverse selection problem associated with lending so that banks can distinguish between risky and safe borrowers. By knowing the characteristics of borrowers, banks make better judgments concerning lending and lend safely. Secondly, sharing borrower information eliminates information differences across banks, such that borrowers are not held up to one bank, and they have less incentive to pursue the high-risk investment, which may lead to higher default probability. Thirdly, information sharing exerts a disciplinary effect on borrowers because they fear that their default information will be available to other banks and they may have to face an outright exclusion from the credit markets. Lastly, information sharing reveals the overall indebtedness of borrowers, so borrowers are not able to over-borrow and end up default. Therefore, sharing of borrower information among banks contributes to lower default rate and promote bank stability.

We also examine the impact of information environment on the relationship between credit information sharing and bank risk. According to the results, we find that mandatory IFRS adoption and greater extent of business disclosure attenuates the impact of credit information sharing on bank risk. These results suggest that, compared to less transparent information environment, credit information sharing has a weaker effect on bank risk in a more transparent information environment. When the information environment is less opaque, the asymmetric information between banks and borrowers becomes less problematic. More borrower information is available and accessible to the public, such that promoting information sharing among banks may be less helpful in reducing bank risk.

Moreover, we explore the impact of banking competition on the relationship between credit information sharing and bank risk. The empirical results show that the impact of credit information sharing on bank risk is more pronounced in the more competitive banking market. Banks in the highly competitive banking market have fewer incentives to screen and monitor their borrowers. When banking market becomes more competitive, the average quality of borrowers decreases. Rejected applicants can continue to apply at other banks, so low-quality applicants are likely to receive credits as more banks compete in the market. Furthermore, when several banks compete fiercely in the credit market, each bank has a small pool of borrowers, such that borrower information is so dispersed compared to the less competitive market. Moreover, banks in less competitive banking market have higher capacity and stronger incentives to screen and monitor, such that borrowers do not pursue risky investment activities. Thus, the problems of adverse selection and moral hazard exacerbate as the banking market becomes more and more competitive. In these regards, our finding suggests that the benefits of information sharing in helping to reduce bank risk tends to be more pronounced in the more competitive banking market.

In chapter 4, our objectives are to explore the impact of credit information sharing on bank-specific stock price crash risk and how, and to what extent, information asymmetry and bank regulations affect it. Studying the sample of 1,402 listed-banks in 55 countries during 2005 to 2013, we conclude that credit information sharing through public credit registries reduces crash risk, whereas the depth of credit information sharing and information sharing through private credit bureaus have no significant effect on crash risk. The result shows that banks are less likely to encounter stock price crash risk in countries with more borrower information sharing through public credit registries.

The negative association between information sharing through public credit registries and crash risk suggests that forcing banks to share borrower information among each other may reduce bank opacity and discourage their loan officers to withhold bad news for an extended period, such that crash risk is reduced. Because bank transparency is enhanced and loan officers refrain from hiding bad news, the unanticipated release of bad news is also less likely to occur and less likely to generate stock price crash. To be more precise, compulsory information sharing can help monitoring loan officers and preventing corruption in lending. Also, borrower information sharing from one bank improves comparability and provides benefits to another bank validating internal risk ratings so that loan officers are less likely to bias their borrower reports. Thus, forcing banks to disclose and share borrower information with each other tends to enhance investors' perception about banks' performance, such that information sharing reduces stock price crash risk.

The insignificant effect of information sharing through private credit bureaus on crash risk suggests that the voluntary exchange of credit information among banks may not be adequate to prevent loan officers from hiding bad news. Banks may self-select themselves into sharing credit information and may share only information that makes them better off.

Moreover, joining the private credit bureaus is not compulsory, and they are less regulated than the public credit registries. Therefore, opaque banks may not join the credit bureaus to share borrower information in the first place.

Furthermore, we examine the effect of information environment on the relationship between credit information sharing and crash risk. In an environment with more transparent information, loan officers have less ability to hide negative information about borrowers because more information is accessible to external investors and loan managers. According to the empirical results, we find that the impact of credit information sharing on crash risk is less pronounced in more transparent information environment proxied by the mandatory IFRS adoption. Therefore, when the information environment is less opaque, borrower information sharing tends to be less helpful in reducing crash risk.

We also examine the impact of banking regulatory environments on the relationship between credit information sharing and crash risk. Bank regulations are usually viewed as external mechanisms implemented by bank regulators to monitor banks and encourage them to be more disciplined. If banks face strict regulatory environments, they are more likely to allocate capital efficiently and have less ability to conceal bad news.

By conducting an empirical analysis, we analyze three aspects of bank regulations, consisting of capital stringency requirements, supervisory power, and private monitoring. Firstly, we find that the relationship between information sharing through public credit registries and crash risk is more pronounced with less stringent capital requirements. If banks are not required to put a substantial amount of their equity at risk, they may not be cautious in lending and might take excessive risk. In this regard, our result suggests that less stringent capital requirements may induce loan officers to behave riskily and conceal bad news, such that forcing banks to share borrower information tends to be more helpful in reducing crash risk.

Secondly, we find that the relationship between information sharing through public credit registries and crash risk is more pronounced with low supervisory power. Bank supervisors need adequately high powers to closely monitor and prevent banks from engaging in undesirable activities, notably complex banking activities. Thus, our result suggests that, when bank supervisors weakly regulate banks, banks may behave opportunistically and hide bad news for an extended period, such that forcing banks to share borrower information is more useful in reducing crash risk.

Thirdly, we find that the relationship between information sharing through public credit registries and crash risk is more pronounced with a low degree of private monitoring. Less emphasizing private monitoring means that banks are not encouraged to disclosure more and accurate information to the public so that investors have fewer abilities and fewer incentives to overcome informational barriers. Thus, banks are opaquer in an environment with a low degree of private monitoring than those in an environment with a high degree. In this regard, our result suggests that forcing banks to share borrower information tends to be more beneficial for an environment with a low degree of private monitoring.

According to the empirical analysis of bank regulations, our findings suggest that, when the banking regulatory environments are weak, it is more useful to reduce crash risk by forcing banks to share borrower information. Among three aspects of bank regulations, our findings also reveal that credit information sharing is much more useful in reducing crash risk with less powerful bank supervisors than less stringent capital requirements and less emphasis on private monitoring. It suggests that the issue of hiding bad news could be more problematic whenever less power is given to bank supervisors to oversee banking sectors.

5.2 Policy Implications

There are various policy implications of this study. Policymakers may focus on establishing and promoting information sharing institutions to enhance information sharing among banks and the availability of credit information. Well-established information sharing institutions can alleviate the information problems faced by banks in the credit market. The information problem between banks and borrowers makes banks reluctant to extend credit. With the improved availability of credit information, it is possible to encourage banks to lend and achieve a better credit allocation in the economy.

Policymakers can design policies that enhance the scope, accessibility, and quality of credit information available through information sharing institutions, especially private credit bureaus. Since private credit bureaus tend to surpass public credit registries in the comprehensiveness of the data and services they provide to lenders, policymakers should not design public credit registries so that it may choke the creation of private credit bureaus. In order to not choke the creation of private credit bureaus, they should consider selectively limiting the scope and/or depth of information provided by the public registry. However, public credit registries can be an effective tool to improve the amount and quality of information available on borrowers in emerging economies with non-existent or under-developed information sharing institutions. While policymakers support the establishment of private credit bureaus, they could frequently regulate these bureaus to ensure data privacy rather than attempting to enhance credit information per se.

When policymakers decide to uphold information sharing among banks, they also need to consider the transparency of the information environment. Our study shows that information environment has a significant implication on the impact of credit information sharing on bank lending, bank risk, and crash risk. When the information environment is very opaque, the information problems become more problematic. Thus, policymakers may improve the situation by encouraging banks to share information among themselves and elevate the quality of credit information available through information sharing institutions.

Moreover, our findings indicate that credit information sharing has no notable impact on bank lending with very weak creditor rights. Some degree of creditor protection is necessary to guarantee the effect of credit information sharing on lending. Therefore, credit information sharing is complementary to the protection of creditors. Policies that promote credit information sharing should also stimulate the development of creditor protection.

Policymakers should also aim at promoting information sharing mechanisms when the banking market is very competitive so that the problem of adverse selection and moral hazard can be less of a concern and banks become more stable amid fierce competition. Our results do not only highlight the importance of bank competition on bank stability, as the literature has extensively shown, but also the influence of bank competition on the beneficial impact of credit information sharing on bank stability.

To prevent stock price crash risk in the stock markets, policies may need to focus on the establishment and improvement of public credit registries and those policies should be designed that force banks to share their borrowers' credit information This compulsory sharing could allow bank regulators to effectively monitor banks' tendency to hoard bad news and to limit the downside risk in the stock market. Moreover, compulsory information sharing mechanism should be implemented in an environment with low information transparency. In addition, when the banking regulatory environments are weak, regulators could encourage banks to be more transparent and disciplined by using compulsory information sharing mechanism, as opposed to voluntary sharing via private credit bureaus. More importantly, the findings in this study could provide useful information for investors and shareholders that are seeking to manage tail risk in the stock market and to investors who want to incorporate crash risk in their portfolio and risk management decisions.

5.3 Suggestions for Future Research

In this study, we use the depth of credit information sharing index from the World Bank's Doing Business to test our predictions in chapter 2, chapter 3 and chapter 4. This index is a good proxy measuring the scope, coverage, and accessibility of credit information available through information sharing agencies in each country. However, this depth index for each country is publicly available only in a single index aggregating six individual features. Thus, it would be helpful if data underlying the depth of credit information index becomes publicly available so that this information can easily be used for research. Also, information on each individual bank's participation in information sharing would be more useful in examining the impact of information sharing on lending.

When the data underlying the depth of credit information sharing index become publicly available, it is also interesting to distinguish the sharing of positive and negative information. Sharing of both types of information reduces credit risk (Jappelli & Pagano 2002). However, dissemination of negative information may reduce banks' profit, and thus carries the risk of an increased probability of a crisis if information sharing does not emerge endogenously among banks (Dell'Ariccia & Marquez 2006). Testing different impact of types of information sharing requires a very careful distinction between the two different mechanisms through which information sharing systems emerge. The depth of the credit information sharing index we use in this thesis summarizes six different features of the information sharing arrangement, including whether the positive or negative information is distributed. However, they are aggregated and not publicly available. Therefore, it would be helpful if data underlying the depth of credit information index and how they have changed since the start of the survey became publicly available so that this information can handily be used for research.

Another possible extension is to distinguish between credit to households and enterprises. This is because household and enterprise credit has different implications for economic activity. Theory and empirical studies document that enterprise credit contributes to economic growth (Levine 2005), whereas credit to households either has no effect of growth (Beck *et al.* 2008) or that it even reduces growth (Jappelli & Pagano 1994). In addition, household and enterprise also differ in the complexity of their balance sheet presenting different information challenges to banks. Thus, we left to future study and answer the question "Does credit information sharing affect lending to households and enterprises in similar ways?

Due to the importance of private credit bureaus, future research extension can examine whether the effect of credit information sharing depends on the extensiveness of information sharing as proxied by the number of private credit bureaus a bank is partnering within a given year. In comparison with a bank partnering with a single private credit bureau, a bank that is a partner of multiple private credit bureaus at a time is, on average, presumably able to make better-informed lending decisions, which, might, in turn affect the volume of loans it grants.

Instead of using an accounting-based risk indicator like Z-Score, future research can employ a market-based indicator like the Distance-to-Default model of Merton (1987). In comparison to the use of accounting-based models, the market-based measure of risk has the following pros: first, market variables are unlikely to be influenced by firm's accounting policies; second, in the efficient markets, stock prices reflect all available information; third, market prices reflect future expected cash flows and this should be more appropriate for use for prediction purposes.

Moreover, we can improve upon our competition measure and make it more efficient than the conventional Lerner index (Koetter *et al.* 2008; Ariss 2010; Koetter *et al.* 2012). Koetter *et al.* (2012) have argued that the conventional way of estimating the Lerner index assumes both profit efficiency (optimal choice of prices) and cost efficiency (optimal choice of inputs by firms). Consequently, the estimated conventional price-cost margins do not correctly measure the true extent of market power (competition). Impliedly, the conventional Lerner index measures "actual" (exercised) market power, while Koetter *et al.* (2012) purpose an adjustment to the conventional Lerner index that results in "efficiency-adjusted Lerner index". Further information about the adjusted-Lerner index can be found in the appendix. Both the Lerner index and the adjusted-Lerner index have their own merits and drawbacks (Clerides *et al.* 2015). Therefore, given the objectives of this research agenda, we leave the adjusted-Lerner index for future research and focus on the Lerner index as the most widely used due to its simplicity and intuitive interpretation.

Although we have controlled for many factors such as bank fixed effects and year fixed effects in our panel data regression, omitted variable bias remain a potential concern. If unobservable factors are not time-invariant – if they move up and down over time within categories in a way that is correlated with the variables included in the regression – then the omitted variable bias still prevail. We have attempted to control such time-varying factors, it is impossible to rule out this possibility of potential time-varying omitted variables. We have employed an instrumental variable approach to account for the problem of potential endogeneity; however, a superior approach to address potential endogeneity due to time-varying omitted variables or simultaneity is to apply a dynamic panel model using the general method of moments instrumental variable (GMM-IV) approach proposed by Arellano and Bond (1991). But because the estimation of GMM-IV approach involves first-differencing the equations, it may render the significance of our main regressor, credit information sharing, because it is quasi-time invariant.

We address the problem of endogeneity by using instrumental variables techniques with the legal origin as one of the instruments for the credit information sharing measure. Yet, although this approach has been popular in the literature, notably after the pioneering work of La Porta *et al.* (1997), it is without criticism. To be specific, La Porta *et al.* (2008) emphasize that "legal origins influence many spheres of lawmaking and regulation, which makes it dangerous to use them as instruments". However, following Barth *et al.* (2009) and Houston *et al.* (2010), we push forward with instrumental variables analysis and, at the same time, acknowledge that our instrumental variables analysis is without criticism.

Beyond the impact in the banking industry, the impact of credit information sharing may carry over to macro-level concerning economic development and poverty reduction.

Unequal access to finance has long been recognized as a critical mechanism for generating persistent income inequality and slower economic growth (Beck *et al.* 2007). Since previous research shows that credit information sharing improves access to credit, creates job and increases the probability of detecting lending corruption (Barth *et al.* 2009; Brown *et al.* 2009; Ayyagari *et al.* 2016), all these would translate into better credit allocation, resulting in higher economic growth and a reduction in poverty.

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Appendix

Appendix A Definition of Data Sources

Name	Definition and Link	Note
BankScope Database (Access via University of Durham)	The Bankscope database, which is provided by Bureau van Dijk and Fitch Ratings, had comprehensive coverage in most countries, accounting for more than 90% of all banking assets in each country globally. Each bank report consists of up to 200 data items and 36 pre-calculated financial ratios from a detailed balance sheet and income statement (BankScope, 2016). https://library.dur.ac.uk/record=b2796117~S1	Expire since November 2016
BankScope Database (Access via Wharton Research Data Services WRDS)	The Bankscope database, which is provided by Bureau van Dijk and Fitch Ratings, had comprehensive coverage in most countries, accounting for more than 90% of all banking assets in each country globally. Each bank report consists of up to 200 data items and 36 pre-calculated financial ratios from a detailed balance sheet and income statement (BankScope, 2016). https://wrds-web.wharton.upenn.edu/wrds/query_forms/navigation.cfm?navId=50	Expire since December 2016
Central Intelligence Agency (CIA)'s The World Fact Book	The World Factbook provides information on the history, people, government, economy, geography, communications, transportation, military, and transnational issues for 267 world entities (CIA 2017). https://www.cia.gov/library/publications/the-world-factbook/fields/2011.html	

Datastream (Access via University of Durham)	Datastream is a largest and comprehensive database providing historical financial information, which includes worldwide coverage of stock market and bond indices, equities, company fundamentals, currencies, interest rate, fixed income securities, derivatives and other key international economic indicators for 175 countries and 60 markets (Datastream, 2016).	
Deposit Insurance Database	http://siteresources.worldbank.org/INTRES/Resources/469232-1107449512766/Deposit_Insurance_Database_July2015.xlsx	
Djankov et al. (2007) Dataset	http://scholar.harvard.edu/files/shleifer/files/jfe_2007__dataset_oct08.xls	
Easterly and Levine (2001) Dataset	http://siteresources.worldbank.org/INTRES/Resources/469232-1107449512766/Lost_Decades_Social_Indicators_and_Fixed_Factors.xls	
International Financial Reporting Standard (IFRS) Data	http://www.ifrs.org/Use-around-the-world/Pages/Jurisdiction-profiles.aspx (IFRS Foundation) http://www.iasplus.com/en/jurisdictions (Deloitte) http://www.adoptifrs.org/countries.aspx (Simon Fraser University in Canada)	
LaPorta et al. (1998) Dataset	http://faculty.tuck.dartmouth.edu/images/uploads/faculty/rafael-laporta/Law_Fin.xls	

LaPorta et al. (1999) Dataset	http://faculty.tuck.dartmouth.edu/images/uploads/faculty/rafael-laporta/Quality_of_Govt.xls	
World Bank's Banking Regulation and Supervision Survey (Version I)	The World Bank's Bank Regulation and Supervision Survey is a unique source of comparable world-wide data on how banks are regulated and supervised around the world. The Version I survey was launched by Barth *et al.* (2001) in 2001 containing information for 117 countries. http://siteresources.worldbank.org/INTRES/Resources/469232-1107449512766/Caprio_2000_banking_regulation_database.xls	
World Bank's Banking Regulation and Supervision Survey (Version II)	The World Bank's Bank Regulation and Supervision Survey is a unique source of comparable world-wide data on how banks are regulated and supervised around the world. The Version II survey, by Barth *et al.* (2006), contains the regulatory environment at the end of 2002 in 152 countries. http://siteresources.worldbank.org/INTRES/Resources/469232-1107449512766/Caprio_2003_banking_regulation_database.xls	
World Bank's Banking Regulation and	The World Bank's Bank Regulation and Supervision Survey is a unique source of comparable world-wide data on how banks are regulated and supervised around the world. The Version III survey, by Barth *et al.* (2008a), contains and describes the regulatory environment in 142 countries in 2005/2006.	Dataset

Supervision Survey (Version III)	http://siteresources.worldbank.org/INTRES/Resources/469232-1107449512766/Banking_regulation_Survey_III_061008.xls	
	http://siteresources.worldbank.org/INTRES/Resources/469232-1107449512766/Caprio_2003_Guide.doc	Survey Questionaire and Guidance
World Bank's Banking Regulation and Supervision Survey (Version IV)	The World Bank's Bank Regulation and Supervision Survey is a unique source of comparable world-wide data on how banks are regulated and supervised around the world. The Version IV compiled by Barth et al. (2013a), provides information on bank regulation and supervision for up to 143 jurisdictions. http://siteresources.worldbank.org/EXTGLOBALFINREPORT/Resources/8816096-1346865433023/8827078-1347152290218/Bank_Regulation.xlsx	Dataset
	http://siteresources.worldbank.org/EXTGLOBALFINREPORT/Resources/8816096-1346865433023/8827078-1347152290218/Guidelines_Questionnaire_sections.pdf	Survey Questionaire and Guidance

World Bank's Doing Business	The Doing Business project provides objective measures of business regulations and their enforcement across 189 economies and selected cities at the subnational and regional level. By gathering and analyzing comprehensive quantitative data to compare business regulation environments across economies and over time, the Doing Business project encourages economies to compete towards more efficient regulation; offers measurable benchmarks for reform; and serves as a resource for academics, journalists, private sector researchers and others interested in the business climate of each economy (World Bank Doing Business 2016). http://www.doingbusiness.org/Custom-Query	
World Bank's Global Financial Development Database (GFDD)	The Global Financial Development is an extensive dataset of financial system characteristics for 203 economies. The database includes measures of (1) size of financial institutions and markets (financial depth), (2) degree to which individuals can and do use financial services (access), (3) efficiency of financial intermediaries and markets in intermediating resources and facilitating financial transactions (efficiency), and (4) stability of financial institutions and markets (stability). http://pubdocs.worldbank.org/en/762771441897023024/GlobalFinancialDevelopmentDatabaseSeptember2015.xlsx	

World Bank's World Development Indicators (WDI)	The WDI database is the primary World Bank collection of development indicators, compiled from officially-recognized international sources. It presents the most current and accurate global development data available, and includes national, regional and global estimates. http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators	
World Bank’s World Governance Indicators (WGI)	The WGI database provides six governance indicators gathered from several survey institutes, think tanks, non-governmental organizations, international organizations, and private sector firms (World Bank 2016). They are constructed from 276 individual variables taken from 31 different sources produced by 25 different organizations. These six composite of WGI are useful for cross-country governance comparison and for evaluating broad trends over time (Kaufmann *et al.* 2011). http://data.worldbank.org/data-catalog/worldwide-governance-indicators	

Appendix B The List of Countries and IFRS Adoption

Country	Effective Date of Mandatory IFRS Adoption
ALGERIA	
ANGOLA	
ARGENTINA	2012
ARMENIA	2011
AUSTRALIA	2005
AUSTRIA	2005
BANGLADESH	1987
BELARUS	2016
BELGIUM	2005
BENIN	
BOLIVIA	
BOSNIA AND HERZEGOVINA	2006
BOTSWANA	2007
BRAZIL	2010
BULGARIA	2005
BURKINA FASO	
BURUNDI	
CAMEROON	
CANADA	2011
CHAD	
CHILE	2010
CHINA	
COLOMBIA	2015
COSTA RICA	2005
COTE D'IVOIRE	
CROATIA	2005
CZECH REPUBLIC	2005
DENMARK	2005
DOMINICAN REPUBLIC	2014
ECUADOR	2010
EGYPT	
EL SALVADOR	2011

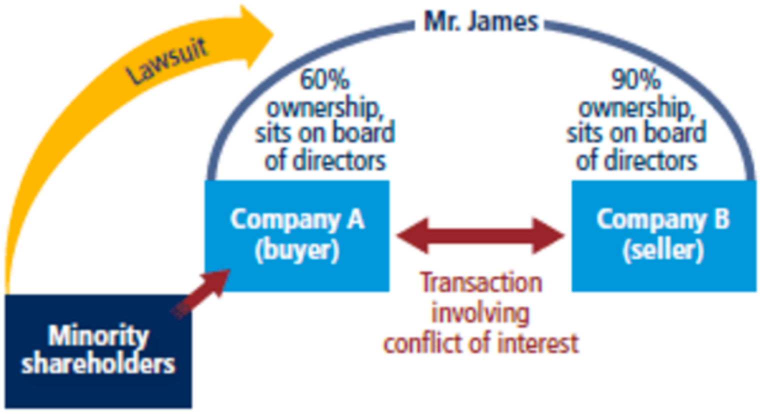
ETHIOPIA	
FINLAND	2005
FRANCE	2005
GERMANY	2005
GHANA	2007
GREECE	2005
GUATEMALA	2008
HONDURAS	
HONG KONG	2005
HUNGARY	2005
INDIA	
INDONESIA	
IRELAND	2005
ISRAEL	2008
ITALY	2005
JAMAICA	2002
JAPAN	2016
JORDAN	1997
KAZAKHSTAN	2005
KENYA	1999
KUWAIT	
KYRGYZSTAN	2003
LATVIA	2005
LEBANON	
LESOTHO	
LITHUANIA	2005
MACEDONIA (FYROM)	2010
MADAGASCAR	
MALAWI	
MALAYSIA	2012
MALI	
MEXICO	2012
MONTENEGRO	
MOROCCO	
MOZAMBIQUE	2010
NAMIBIA	2005
NEPAL	2016
NETHERLANDS	2005
NEW ZEALAND	2007
NICARAGUA	

NIGER	
NIGERIA	2012
NORWAY	2005
OMAN	1986
PAKISTAN	2013
PANAMA	
PAPUA NEW GUINEA	
PARAGUAY	2014
PERU	2012
PHILIPPINES	
POLAND	2005
PORTUGAL	2005
REPUBLIC OF KOREA	2011
REPUBLIC OF MOLDOVA	2011
ROMANIA	2005
RUSSIAN FEDERATION	2015
SAUDI ARABIA	2017
SENEGAL	
SIERRA LEONE	2006
SINGAPORE	2018
SLOVAKIA	2005
SLOVENIA	2005
SOUTH AFRICA	2005
SPAIN	2005
SRI LANKA	2012
SWEDEN	2005
SWITZERLAND	
SYRIAN ARAB REPUBLIC	
THAILAND	
TOGO	
TUNISIA	
TURKEY	2008
UGANDA	1998
UKRAINE	2012
UNITED ARAB EMIRATES	2012
UNITED KINGDOM	2005
UNITED REPUBLIC OF TANZANIA	2004
UNITED STATES OF AMERICA	
URUGUAY	2009

VENEZUELA	2005
ZIMBABWE	1996

Appendix C The Components of The Business Extent of Disclosure Index (BDI)

Figure 5-1: How well are minority shareholders protected from conflicts of interest?



Source: World Bank's Doing Business (2016)

<u>Assumptions about the business</u>

The business (Buyer):

- • Is a publicly traded corporation listed on the economy's most important stock exchange. If the number of publicly traded companies listed on that exchange is less than 10, or if there is no stock exchange in the economy, it is assumed that Buyer is a large private company with multiple shareholders.
- • Has a board of directors and a chief executive officer (CEO) who may legally act on behalf of Buyer where permitted, even if this is not specifically required by law.
- • Has a supervisory board (applicable to economies with a two-tier board system) on which 60% of the shareholder-elected members

have been appointed by Mr. James, who is Buyer's controlling shareholder and a member of Buyer's board of directors.

- • Has not adopted any bylaws or articles of association that differ from default minimum standards and does not follow any nonmandatory codes, principles, recommendations or guidelines relating to corporate governance.
- • Is a manufacturing company with its own distribution network.

Assumptions about the transaction

- • Mr. James owns 60% of Buyer and elected two directors to Buyer's five-member board.
- • Mr. James also owns 90% of Seller, a company that operates a chain of retail hardware stores. Seller recently closed a large number of its stores.
- • Mr. James proposes that Buyer purchase Seller's unused fleet of trucks to expand Buyer's distribution of its food products, a proposal to which Buyer agrees. The price is equal to 10% of Buyer's assets and is higher than the market value.
- • The proposed transaction is part of the company's ordinary course of business and is not outside the authority of the company.
- • Buyer enters into the transaction. All required approvals are obtained, and all required disclosures made (that is, the transaction is not fraudulent).
- • The transaction causes damages to Buyer. Shareholders sue Mr. James and the other parties that approved the transaction.

Extent of disclosure index

The extent of disclosure index has five components:

- • Which corporate body can provide legally sufficient approval for the transaction. A score of 0 is assigned if it is the CEO or the managing director alone; 1 if the board of directors, the supervisory board or shareholders must vote and Mr. James is permitted to vote; 2 if the board of directors or the supervisory board must vote and Mr. James is not permitted to vote; 3 if shareholders must vote and Mr. James is not permitted to vote.
- • Whether it is required that an external body, for example, an external auditor, review the transaction before it takes place. A score of 0 is assigned if no; 1 if yes.
- • Whether disclosure by Mr. James to the board of directors or the supervisory board is required.(1) A score of 0 is assigned if no disclosure is required; 1 if a general disclosure of the existence of a conflict of interest is required without any specifics; 2 if full disclosure of all material facts relating to Mr. James's interest in the Buyer-Seller transaction is required.
- • Whether immediate disclosure of the transaction to the public, the regulator or the shareholders is required. A score of 0 is assigned if no disclosure is required; 1 if disclosure on the terms of the transaction is required but not on Mr. James's conflict of interest; 2 if disclosure on both the terms and Mr. James's conflict of interest is required.
- • Whether disclosure in the annual report is required. A score of 0 is assigned if no disclosure on the transaction is required; 1 if disclosure on the terms of the transaction is required but not on Mr. James's conflict of interest; 2 if disclosure on both the terms and Mr. James's conflict of interest is required.

- The index ranges from 0 to 10, with higher values indicating greater disclosure. In Poland, for example, the board of directors must approve the transaction and Mr. James is not allowed to vote (a score of 2). Poland does not require an external body to review the transaction (a score of 0). Before the transaction Mr. James must disclose his conflict of interest to the other directors, but he is not required to provide specific information about it (a score of 1). Buyer is required to disclose immediately all information affecting the stock price, including the conflict of interest (a score of 2). In its annual report Buyer must also disclose the terms of the transaction and Mr. James's ownership in Buyer and Seller (a score of 2). Adding these numbers gives Poland a score of 7 on the extent of disclosure index.

Appendix D Adjusted-Lerner Index

Koetter *et al.* (2012) point out that the conventional computation of Lerner Index does not measure the true extent of market power. They argue that the Lerner index approach assumes both profit efficiency (optimal choice of prices) and cost efficiency (optimal choice of inputs by firms). Thus, they propose a new form of the efficiency-adjusted Lerner Index:

$$Adjusted\ Lerner_{it} = \frac{\pi_{it} + tc_{it} - MC_{TA_{it}} * q}{\pi_{it} + tc_{it}} \quad \text{(A-1)}$$

Where π_{it} is the bank i's profit at time t; tc_{it} is the total cost; $MC_{TA_{it}}$ is the marginal cost and q is the total output. Similar interpretation to the conventional Lerner index, the efficiency-adjusted Lerner index ranges from zero to one with larger values indicating less competition (greater market power). This approach has been used by Ariss (2010), Koetter *et al.* (2008) and Koetter *et al.* (2012).

Appendix E Distance-To-Default (DtD) Model

Furthermore, the Distance-To-Default will be calculated by incorporating both market-based and accounting-based variables. The model is used to estimate the distance-to-default, which is the distance between the expected value of the firm's assets and the default point and then divides this difference by the estimated volatility of the firm in a time horizon. The distance-to-default is simply the number of standard deviations that the firm is away from default The firm is considered as default when the value of firm's asset falling below the default point. The face value of the debt is regarded as the default point in the Merton's Model. The larger the number is in the Distance-to-default, the less chance the company will default. And the distance-to-default is further used to generate the probability of default of a firm. More detail and its calculation can be found in the appendix.

To calculate the distance-to-default, we first need to find the value of the firm's asset and the asset's volatility from the market value of the firm's equity and the equity's volatility, given the outstanding and maturity of debt. The maturity of the debt is chosen and the debt's book value is set to equal the face value of the debt. To calculate the default probability, the distance to default is substituted into a cumulative density function to calculate the probability that the value of the firm will be less than the face value of debt at the maturity of the debt. Further detail of the calculation will be elaborated below.

The foundation for the Merton DD model lies with the structural model of default developed by Black and Scholes (1973) and Merton (1974). Merton extended the work of Black and Scholes (1973) on option pricing theory in the default prediction of the firm, along with certain strong assumptions. Later in late 1980s, KMV Corporation developed the application of Merton's model to forecast default of the firm and the model becomes known as the KMV-Merton Model. This model views equity as a standard call option on the assets of a firm, with a strike price equal to the face value of the debt with T as a time-to-maturity. At time T, equity holders exercise their option and pay off the debt holders if the value of the firm's assets is greater than the face value of its debt. Otherwise, if the value of the assets is insufficient to fully repay the firm's debts, the call option becomes worthless, and equity holders let it expire. In this scenario, the firm files for bankruptcy, and ownership is assumed to be transferred to the debt holders at no cost, whereas the payoff for equity holders is zero (Fu et al. 2014). Thus, the probability of bankruptcy is the probability that the call option will expire worthless (when the value of asset < the face value of the debt at time T).

According to Bharath and Shumway (2008), the Merton DD model estimates the market value of debt by applying the classic Merton (1974) bond pricing model. The Merton model makes two particularly important assumptions. The first is that the total value of a firm follows geometric Brownian motion as followed:

$$dV_A = \mu V_A dt + \sigma_A V_A dW \quad \text{(A-2)}$$

Where V_A is the total value of the firm, μ is the expected continuously compounded return on V_A, σ_A is the volatility of firm value and dW is a standard Wiener process. The second critical assumption of the Merton model is that the firm has issued just one discount bond maturing in T periods. Under these assumptions, the equity of the firm is a call option on the underlying value of the firm with a strike price equal to the face value of the firm's debt and a time-to-maturity of T. Furthermore, the value of equity as a function of the total value of the firm can be described by the Black-Scholes-Merton Formula. By put-call parity, the value of the firm's debt is equal to the value of a risk-free discount bond minus the value of a put option written on the firm, again with a strike price equal to the face value of debt and a time-to-maturity of T.

Given the assumption of assets distributed following a Generalized Brownian Motion, the application of the standard Black–Scholes option pricing formula (Black and Scholes, 1973) yields the closed-form expression showing that the equity value of a firm satisfies:

$$V_E = V_A N(d_1) - De^{-rT} N(d_2) \quad \text{(A-3)}$$

Where V_E is the market value of the firm's equity, D is the face value of the firm's debt, r is the instantaneous risk-free rate under risk-neutrality, $N(*)$ is the cumulative standard normal distribution function. And d_1 and d_2 are expressed as followed:

$$d_1 = \frac{lN\left(\frac{V_A}{D}\right) + \left(r + \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}} \quad \text{(A-4)}$$

$$d_2 = d_1 - \sigma_A\sqrt{T} \quad \text{(A-5)}$$

The Merton DD model makes use of two important equations. The first is the Black-Scholes-Merton Equation (13), expressing the value of a firm's equity as a function of the value of the firm. The second links the volatility of the firm's value (σ_A) to the volatility of its equity (σ_E). Under Merton's assumptions the value of equity is a function of the value of the firm and time, so it follows directly from Ito's lemma that

$$\sigma_E = \left(\frac{V_A}{V_E}\right)\frac{\partial V_E}{\partial V_A}\sigma_A \tag{A-6}$$

In the Black-Scholes-Merton model, it can be shown that $\frac{\partial V_E}{\partial V_A}$ is equal to $N(d_1)$, so that under the Merton model's assumptions, the volatilities of the firm and its equity are related by

$$\sigma_E = \left(\frac{V_A}{V_E}\right)N(d_1)\sigma_A \tag{A-7}$$

And d_1 is defined as above in the equation (14)

The Merton DD model basically uses these two nonlinear equations, (13) and (17), to translate the value and volatility of a firm's equity into an implied probability of default. In most applications of the Black-Scholes-Merton model, it describes the unobserved value of an option as a function of four variables that are easily observed (strike price, time-to-maturity, underlying asset price, and the risk-free rate) and one variable that can be estimated (volatility). However, in the Merton DD model, the value of the option is observed as the total value of the firm's equity (V_E), while the value of the underlying asset (or V_A which is the total value of the firm in the Merton DD Model) is not directly observable.

Thus, V_A and σ_A are not directly observable in the Merton DD model and must be recovered by solving the equation (13) and (17) simultaneously. Once the numerical solution of both V_A and σ_A are obtained, the distance-to-default can be calculated as followed:

$$DtD = \frac{lN\left(\frac{V_A}{D}\right) + \left(\mu - \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}} \tag{A-8}$$

where μ is an estimate of the expected annual return of the firm's assets. The corresponding implied probability of default, sometimes called the expected default frequency (or EDF), is

$$\pi_{MERTON} = N(-DtD) = N\left(-\frac{lN\left(\frac{V_A}{D}\right) + \left(\mu - \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}}\right) \tag{A-9}$$

DtD can be interpreted as the number of standard deviations the value of a firm's asset is away from its default point. This standardization across firm size and volatility can be used to rank firms in terms of their relative credit worthiness. The three key inputs in calculating the DtD (market capitalization, debt, and the volatility of equity) implies that it can be influenced by the leverage ratio (debt/(equity + debt)) and volatility of the firm. A higher value of DtD can be obtained either because the leverage of the firm is low or because the volatility is low or both (Fig. 3).

The Distance-to-default is recovered implicitly from observed information from the balance sheet and market price of firm's liabilities. The calculation of distance-to-default is made on a yearly basis. The value of the firm's equity (V_E) is computed as the yearly average of daily market capitalization (number of common shares * share prices). The volatility of the firm's equity (σ_E) is based on the daily stock returns. Following Fu et al. (2014), the volatility is calculated as the standard deviation of daily stock returns multiplied by the square root of the average number of trading days in the year (set at 252 trading days).

Using this model to quantify distance to default requires some practical compromises. The real debt contracts are not all written with a single terminal date. What then about debt of longer maturity? At longer time horizons, if there is trend asset growth, default becomes relatively unlikely. So this suggests that longer term debt should not have such a big impact on default probabilities (Milne 2014).. To overcome this problem, a common procedure used by Moody's KMV (Vasicek, 1984) and also employed here, is to adopt a one-year horizon (T = 1), but to weight longer term debt (with maturity > 1 year) at only 50% of face value. The default point will then be equal to the face value of short-term liabilities plus a half of the long-term liabilities. In other words, debt (D) is calculated as 100% of deposits and short term debt and 50% of long term debt. This meant that insurance liabilities and also trading liabilities (other than short term unsecured and repo funding) had a zero weighting.

In order to obtain the value of firm's assets (V_A) and asset volatility (σ_A), the two nonlinear simultaneous equation (13) and (17) must be solved, given the observed debt (D) and equity's value (V_E) and volatility (σ_E). The procedure is outlined in the previous section. The description is shown on the table below.

Parameter	**Symbol**	**Notes**
Volatility of (common) Equity	σ_E	Using historical stock return data
Market Value of (common) Equity	V_E or E	Share Price * Shares Outstanding (Market Capitalization)
Face Value of Debt (Default Point)	D or F	100% of deposits and short term debt and 50% of long term debt
Risk-Free Interest Rate	r	The choice of the 3 Month Treasury Bill as the risk free rate is very common but not universal. Some choose 1 Month Treasury Bills (4 week) where these are available
Time	T	Liabilities will mature in 1 year
Market Value of Assets	V_A or V or A	Option-Pricing Model
Volatility of Assets	σ_A or σ_V or σ	Option-Pricing Model

Appendix F Model Selection and Diagnostic Tests

We conduct model selection tests and several diagnostic tests to choose an appropriate estimation technique. In each chapter, all the tests are applied to the equations without interaction terms and the chosen estimation techniques are then applied to the rest of equations with interaction terms. Adding interaction terms would not significantly change the overall results of the tests much. Specifically, in Chapter 2, all tests are applied to Equation (2-2) with no interaction terms and the chosen estimation techniques are then applied to Equation (2-3) and Equation (2-4).. In Chapter 3, all the tests are applied to Equation (3-9) that does not include interaction terms and the chosen estimation technique are then applied to Equation (3-10) and (3-11). Lastly, in Chapter 4, all the tests are applied to Equation (4-8) and the chosen estimation techniques are then applied to Equation (4-9), (4-10), (4-11) and (4-12).

A starting point is to test whether we can estimate a pooled ordinary least squares (OLS) regression. The objective of pooling a time series of cross-sections is to widen the database in order to get better and more reliable estimates of the parameters of the model. But we must know whether we can pool data or not. The OLS estimators are biased and inconsistent if the individual effects present in the regression. Thus, we perform a poolability test. In other words, we test for the presence of individual effects, α_i, in our regression model. Formally, the poolability test has its null hypothesis the OLS model, where H_0: $\alpha_i = 0$ for i = 1, 2, 3…., N. Its alternative hypothesis is the fixed-effect (FE) model. We consider the F statistics according to the construction principle:

$$F_{1-way} = \frac{(ESS_R - ESS_U)/(N-1)}{ESS_U/((T-1)N-K)} \tag{5-1}$$

where ESS_R denotes the residual sum of squares under the null hypothesis, ESS_U the residual sum of squares under the alternative. Under H_0, the statistic F_{1-way} is distributed as F with $(N-1, (T-1)N-K)$ degrees of freedom. The two sums of squares evolve as intermediate results from OLS and from FE estimation. When the null hypothesis is rejected that all α_i are zero, the OLS estimates suffer from the problem of omitted variables and they are biased and inconsistent under the presence of the individual effects.

Next, we perform the Hausman test to choose between fixed-effect (FE) model and random-effect (RE) model. The fundamental distinction between FE and RE models is the assumption that the individual effects, α_i, are correlated or uncorrelated with the regressors. The regressors are *DEPTH* and other bank- and country-specific controls. In the FE model, the α_i are permitted to be correlated with the regressors, while continuing to assume that these regressors are uncorrelated with the idiosyncratic error $\varepsilon_{i,t}$. In contrast, the RE model assumes that α_i is purely random and uncorrelated with the regressors. Thus, to decide which model to use, we perform the Hausman test.

The Hausman principle can be applied to all hypothesis testing problems, in which two different estimators are available, the first of which $\tilde{\beta}$ of the FE model is efficient under the null hypothesis, however inconsistent under the alternative, while the other estimator $\check{\beta}$ from the RE model is consistent under both hypotheses. The construction of Hausman test statistic is based on $\Phi = \tilde{\beta} - \check{\beta}$. Because of the consistency of both estimators under the null, this difference, Φ, will converge to zero, while it fails to converge under the alternative. According to Hausman, the statistic $\omega = \Phi'(var\ \Phi)^{-1}\Phi$, where $var\ \Phi = var\ \tilde{\beta} - var\ \check{\beta}$ follows from the known properties of both estimators under the null hypothesis and from uncorrelatedness. The statistic ω is distributed as χ^2 under the null hypothesis, with degrees of freedom corresponding to the dimension of β. The rejection of the null hypothesis shows that individual effects are nor random and we should use the fixed-effect model.

Moreover, we test for the groupwise heteroscedasticity in the residuals of the fixed-effects regression by performing a modified Wald test, proposed by Baum (2001). When the error process is homoscedastic (or constant variance) within cross-sectional units, but its variance differs across units we call this groupwise heteroskedasticity. The standard error component assumes that the regression disturbances are homoskedastic with the same variance across time and individuals. This may be a restrictive assumption for panels. The null hypothesis specifies that:

$$H_0: \sigma_i^2 = \sigma^2 \tag{5-2}$$

for i = 1, 2, 3…., N_g, where N_g is the number of cross-sectional units. The resulting test statistic is distributed Chi-squared under the null hypothesis of homoscedasticity. When heteroskedasticity is present, the standard errors of the estimates will be biased. The rejection of the null hypothesis suggests that the heteroskedasticity exists. However, we can deal heteroscedasticity by estimating standard errors that are robust to conditional heteroscedasticity. The robust standard errors are sometimes called the White-Huber standard errors or the Sandwich estimators of variance.

Because serial correlation in linear panel-data models biases the standard errors and causes the results to be less efficient, we also need to identify serial correlation in the idiosyncratic error term in a panel-data model. We rely on the method discussed by Wooldridge (2010) and implemented by Drukker (2003). The method uses the residuals from a regression in first-differences as shown in the equations below.

$$Y_{it} - Y_{it-1} = (X_{it} - X_{it-1})\beta + (\varepsilon_{it} - \varepsilon_{it-1}) \quad (5\text{-}3)$$

$$\Delta Y_{it} = \Delta X_{it}\beta + \Delta\varepsilon_{it} \quad (5\text{-}4)$$

Where Δ is the first-difference operator. The procedure begins by estimating the parameters β by regressing ΔY_{it} on ΔX_{it} and obtaining the residuals $\hat{\varepsilon}_{it}$. Central to this procedure is Woodridge's observation that, if the ε_{it} is not serially correlated, then the residuals from the regression of the first-differenced variables should have an autocorrelation of -0.5 [i.e. $corr(\Delta\varepsilon_{it}, \Delta\varepsilon_{it-1})$ = -0.5]. Given this observation, the procedure continues regressing the residuals $\hat{\varepsilon}_{it}$ from the regression with first-differenced variables on their lagged residuals and tests whether the coefficient on the lagged residuals is equal to -0.5. Under the null hypothesis of no serial correlation, the coefficient on the lagged residuals in a regression of the lagged residuals on the current residuals should equal to -0.5 (Drukker 2003; Wooldridge 2010). The rejection of the null hypothesis indicates that the errors are autocorrelated. However, we can adjust standard errors by clustering at the panel level to account for the within-panel correlation in the regression of $\hat{\varepsilon}_{it}$ on $\hat{\varepsilon}_{it-1}$.

Appendix G Instrumental Variables Approach

We select instrumental variables for credit information sharing measure based on the literature on law and finance. These variables are legal origin, ethnic fractionalization and latitude. These variables have been previously used in Barth *et al.* (2009), Houston *et al.* (2010), Büyükkarabacak and Valev (2012) and Fu *et al.* (2014) as instruments.

According to law and finance perspective, the literature (La Porta *et al.* 1999; Beck *et al.* 2003) shows that historical legal origins help explain the international differences in the financial system and development today. Legal origins can be thought of as exogenous because it was imposed by colonial power in many emerging countries (La Porta *et al.* 1999; Acemoglu & Johnson 2005). Moreover, Djankov *et al.* (2007) also find that that legal origins have a pronounced impact in credit market institutions. In addition, the legal origin itself does not directly affect bank lending, but it may have an indirect impact through other channels such as institutions and regulations. Therefore, we include a dummy of legal origin, which take a value of one if legal origin is English and zero otherwise. According to Djankov *et al.* (2007), the English legal origin consists of the common law of England and its former colonies. Other legal origins include: first is the German legal origin consisting of the laws of the German countries in Central Europe and in East Asia, where the German law was imposed on; second is the French legal origin consists of the civil law of France, of countries Napoleon conquered, and of their former colonies; third is the Nordic legal origin consisting of the laws of the Scandinavian countries; and last is the group of socialist countries.

We use ethnic fractionalization as one of instruments because Easterly and Levine (1997) shows that ethnic diversity explains difference in public policies across country. Economies with greater ethnic diversity tend to choose institutions that allow those in power to expropriate resources from others (Easterly & Levine 1997; Beck *et al.* 2003, 2006a). We use latitude as another instrument based on the theory of endowment. The theory of endowment suggests that geographical location and the disease environment help shape the political and financial institutional development (Acemoglu *et al.* 2001; Beck *et al.* 2003). Specifically, Beck *et al.* (2003) provide strong evidence that geographical endowment has substantial impacts on the formation of long-lasting institutions that shape the financial development.