Three Essays on the Global Financial System

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Declaration

I declare that this thesis has not been submitted as an exercise for a degree at the University of Dublin or any other University and that this thesis is entirely my own and my co-authors' work.
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Yannick Timmer

Short Non-Technical Summary

This thesis comprises of three essays on the *Global Financial System*. The research centers on international financial markets and the intersection between finance and macroeconomics. The thesis uses newly available micro data to answer questions that previously could not have been answered without such datasets.

The first essay documents that different institutional investors exhibit heterogenous investment behavior in financial markets. While banks and investment funds are pro-cyclical investors, who buy after price increases and sell after price declines, insurance companies and pension funds act counter-cyclically. The analysis is conducted with a newly available dataset from the Deutsche Bundesbank which provides security-level holdings information of all investors domiciled in Germany from 2005 until 2014. I show that balance sheet constraints can be made responsible for differential investment behavior across institutional investors. While banks and investment funds financial constraints tighten when they suffer losses on their security holdings, insurance companies and pension funds are more resilient. I make use of within sector variation in the financial constraint to show that tighter financial constraints are associated with more pro-cyclical investment behavior. In this essay, I also highlight a new explanation why it can be rational for banks and investment funds to act in this pro-cyclically manner and I provide supporting empirical evidence. When security prices exhibit a short-term momentum component, banks and investment funds may be incentivized to act pro-cyclically to avoid short-term losses which would tighten their constraints.

In the second essay my co-authors Harald Hau, Peter Hoffmann, Sam Langfield and I use new regulatory data to reveal extensive discriminatory pricing in the foreign exchange derivatives market, in which dealer-banks and their non-financial clients trade over-the-counter. Our analysis draws on new data available under the European Market Infrastructure Regulation (EMIR), which forms the largest transaction-level dataset on derivatives available globally. In this dataset, we observe the identity of both counterparties to each trade, as well as the contract characteristics. For each transaction, we compute the spread as the difference between the contractual forward rate and the mid-price from Thomson Reuters Tick History (TRTH). This allows us to compare execution quality across clients, conditional on contract characteristics. After controlling for contract characteristics, dealer fixed effects, and market conditions, we find that the client at the 75th percentile of the spread distribution pays an average of 30 pips over the market mid-price, compared to competitive spreads of less than 2.5 pips paid by the bottom 25% of clients. Higher spreads are paid by less sophisticated clients. However, trades on multi-dealer request-for-quote platforms exhibit competitive spreads regardless of client sophistication, thereby eliminating discriminatory pricing.

In the final essay my co-authors Romain Duval, Gee Hee Hong and I study the role of financial frictions in explaining the sharp and persistent productivity growth slowdown in advanced economies after the 2008 global financial crisis. Using a rich cross-country, firm-level data set and exploiting variation in pre-existing firm-level exposure to the crisis, we find that the combination of pre-existing firm-level financial fragilities and tightening credit conditions made an important contribution to the post-crisis productivity slowdown. Specifically: (i) firms that entered the crisis with weaker balance sheets experienced decline in total factor productivity growth relative to their less vulnerable counterparts after the crisis; (ii) this decline was larger for firms that faced a more severe tightening of credit conditions; (iii) financially fragile firms cut back on intangible capital investment compared to more resilient firms, which is one among several plausible channels through which financial frictions undermined productivity. All of these effects are highly persistent and quantitatively large − possibly accounting on average for about a third of the post-crisis slowdown in within-firm total factor productivity growth. Furthermore, our results are not driven by more vulnerable firms being less productive or having experienced slower productivity growth before the crisis, or differing from less vulnerable firms along other dimensions.

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Contents

List of Tables

List of Figures

Chapter 1

General Introduction

1.1 Brief Overview

This dissertation is a collection of three central essays that relate to questions in the field of international financial markets and the intersection between finance and macroeconomics. The nature of the research is to use microeconomic data to answer questions which are important for the macroeconomy.

The three essays are linked, the first two focus only on the behavior of various players on financial markets. While both essays suggest an effect on the macroeconomy, the effect of financial frictions on the macroeconomy is only provided in the third essay. Essentially, the use of micro data to answer macroeconomic questions is the central theme recurring in all three essays.

In chapter 2, I contribute to the empirical literature on the investment behavior of financial institutions. Specifically, I establish that banks and investment funds exhibit a pro-cyclical investment behavior on debt capital markets and insurance companies and pension funds act counter-cyclically. Previous work mostly focuses on only one type of investor and concludes that they are destabilizing the market by acting in a pro-cyclical way. In contrast, I consider different types of investors and I show that insurance companies and pension funds are the ones that are on the other side of the trade when banks and investment funds act pro-cyclically.

Without the availability of security-level holdings data for different kinds of institutions, heterogenous investment behavior cannot be established. By using the Microdatabase Security Holdings Statistics I can shed light on these questions.

I estimate a panel regression where I regress the change in the nominal holdings of each investor type on the lagged price change and the respective institution type dummies. The identification is coming from a within-security comparison which I obtain by including *security$*$time* fixed effects. *security$*$time* allow me control for all observed and unobserved security-specific characteristics that could drive the aggregate investment behavior of all institutional investors in a given point in time for a specific security. Therefore, I can observe how the security is changing hands *across* institutional investors in response to a price change.

In chapter 3, I focus on a different part of the financial markets, i.e. the over-the-counter derivatives markets. My co-authors and I are interested in the issue of price discrimination in financial markets. We use regulatory data on foreign exchange forward contracts traded between non-financial corporates and banks traded in over-the-counter markets to study this topic.

We find extremely large discrimination in the exchange rate non-financial corporates pay relative to the competitive interdealer exchange rate. In particular, the corporate at the 75th percentile of the distribution pays roughly 12 times as much as the corporate at the 25th percentile of the distribution.

In the second step we ask the question what explains this discrimination. We test the prediction from OTC search models that more sophisticated firms obtain tighter spreads than unsophisticated firms. Non-financial corporates mainly use these forwards to hedge their currency risk. This means that users of foreign exchange derivatives are on the one hand very sophisticated companies, but on the other hand there are also many small and unsophisticated companies who are using these contracts.

We use various proxies of sophistication to test the hypothesis that lower sophistication is associated with higher spreads and we find overwhelming evidence in favor of this hypothesis. For instance, we find that small firms, with less experienced on OTC markets which have few counterparties pay significantly higher spreads.

An alternative to negotiating trades bilaterally with a bank is to use a request for quote multi dealer trading platform. We show that when firms trade through these multi dealer platforms they pay significantly lower spreads because it induces competition among dealers. This effect is larger for unsophisticated firms than for sophisticated and completely eliminates discriminatory pricing.

We also test whether dealers make use of the opacity of OTC markets to extract rents. Banks do not fully pass through recent exchange rate movements if they would be beneficial for the firm, which results in higher spreads. We do not find this effect when firms trade through multi dealer trading platform.

In chapter 4 my co-authors and I focus on the effect of finance on the macroeconomy. We test whether corporate financial vulnerabilities can be made responsible for the recent low productivity growth. We make use of a difference-in-difference strategy around the Lehman bankruptcy to show that firms that had more debt maturing in 2008, when the crisis hit, had a stronger decline in productivity growth than other firms. We show that the effect of rollover risk on productivity growth was stronger in countries where credit conditions tightened more and for firms that had relationships with banks that were harder hit by the Lehman shock. A back of the envelope calculation suggests that the effect of corporate financial vulnerabilities can account for about one third of the post-crisis within-firm productivity growth slowdown. One potential channel through which rollover risk can undermine productivity growth is through investment in intangible assets, like research and development or software. In order to test this channel, we repeat the same analysis but replace productivity growth with investment in intangible assets and we indeed find that firms that had more debt maturing in the crisis reduced their intangible investment by more than other firms.

Of course, for this paper it is crucial that our treatment variable is not correlated with other variables that affect productivity but which are not related to financial frictions. First, we believe that conceptually the debt that matures in the crisis is a relatively exogenous variable as the 2008 financial crisis was an unexpected event which firms did not anticipated so that they could not schedule their debt accordingly. Second, there is no difference in the productivity growth trend and in the level across firms with different amounts of debt maturing in the crisis. Third, we conduct a placebo test during the early 2000s recession. Given that there was a recession but no banking crisis we would expect no effect across firms with different amounts of debt maturing. While we see that productivity, growth drops on average after the 2000s recession, there is no differential impact across firms with different levels of debt maturing.

Lastly, chapter 5 summarises the overall findings and provides general conclusions of this thesis, along with offering suggestions for future research.

Chapter 2

Cyclical Investment Behavior across Financial Institutions[1]

[1]This is a slightly revised version of the article that is published in the *Journal of Financial Economics*.

2.1 Introduction

Do all institutional investors exhibit similar investment behavior on debt capital markets? Which institutions are stabilizing the market and which are amplifying price dynamics? What drives differences in behavior across financial institutions? To answer these questions, I explore a unique security-by-security holdings dataset provided by the Deutsche Bundesbank.

I present evidence that banks and investment funds respond pro-cyclically to price changes, i.e. they buy securities whose prices are rising and sell them when prices are falling. In contrast, insurance companies and pension funds are counter-cyclical investors, i.e. they buy when prices are falling and sell when prices are rising. In the baseline specification, I regress the percentage change in nominal holdings of the debt security of each sector on the lagged percentage price change of these securities, controlling for observed and unobserved time-invariant security characteristics as well as unobserved and observed time-specific factors. I find that a 10 percent price decrease in the last quarter is associated with a 1.4 percent and 3.6 percent reduction in the nominal amount held by investment funds and banks, respectively. In contrast, insurance companies and pension funds increase their nominal amount held by 4.3 percent when the price of a security dropped by 10 percent in the previous quarter.

This behavior may be attributed to differences in the fragility of the balance sheet structure of these sectors. This can be confirmed by exploiting within-sector variation in the balance sheet constraints. First, the pro-cyclical investment behavior is stronger for banks that are relatively less capitalized. Second, investment funds that face more outflows act more pro-cyclically relative to other investment funds. Third, the counter-cyclical investment behavior of insurance companies and pension funds is weaker when their negative duration gap rises.

I also present evidence that banks' and investment funds' balance sheet constraints tighten when they suffer losses on their security holdings. While losses on the security holdings of investment funds lead to outflows, banks' capital constraints tighten when they suffer losses on their security holdings. Since banks and investment funds are averse to tightening constraints and price changes exhibit a short-term momentum factor, pro-cyclical investment behavior can be rational. In contrast, the liability side of insurance companies and pension funds is relatively more stable and movements in their balance sheets are relatively orthogonal to economic and financial conditions. This makes insurance companies and pension funds more capable of absorbing losses on a short-term horizon and enables them to act in a counter-cyclical fashion.

The pro-cyclical investment behavior of investment funds and banks resulted in relatively mild losses on their security holdings during the European sovereign debt crisis. Although insurance companies and pension funds suffered severe losses on their security holdings during the sovereign debt crisis, they outperformed banks and investment funds in the medium term. More generally, while bond prices fall at short horizons after insurance companies and pension funds have bought them, they revert after several quarters, leading to larger capital gains in the medium run. In contrast, bond prices rise at short horizons after banks and investment funds have acquired them but fall in the medium run.

In order to shed light on these questions, security-level data is indispensable. In this paper I use comprehensive, regulatory security-by-security holdings data provided by the Deutsche Bundesbank (the German central bank) covering the period from 2005 Q4 through 2014 Q4. This study is the first that uses security-level data of the German Microdatabase Security Holdings statistics for bank and non-bank financial institutions and their investment behavior in debt securities.[2] The holdings include both foreign and domestic as well as government and corporate securities. I contrast the buying behavior of the three largest groups of institutional investors: banks; investment funds; and insurance companies and pension funds. By examining the three sectors jointly, I can investigate the investment behavior of banks, investment funds and insurance companies and pension funds in the same security at a given point in time.

Theory yields a variety of predictions about the buying behavior of capital market participants. The standard efficient market hypothesis claims that asset prices must reflect all available information due to the existence of arbitrageurs (Fama, 1965; Friedman, 1953). While banks may be forced to sell undervalued assets due to margin calls, non-levered institutional investors may stabilize the market by buying up fire-sold assets in order to benefit from future price gains (Shleifer and Vishny, 1992). In contrast, it might also be rational to speculate on price increases so that prices can be pushed away from fundamentals (DeLong et al., 1990b; Abreu and Brunnermeier, 2003). However, despite its importance for macro-prudential policy and financial stability, empirical evidence on who is

[2] Abbassi et al. (2016) and Buch et al. (2016) focus on banks' investment behavior in debt securities. Domanski et al. (2017) use aggregate data for German insurance companies and pension funds.

buying and selling as a response to price changes has been elusive due to a lack of granular data.

One contribution of this paper is to identify insurance companies and pension funds as counter-cyclical investors who "lean against the wind" by buying securities when prices are falling and selling them when prices are rising.[3] Due to the market clearing condition, for every pro-cyclical investor there needs to be a counter-cyclical investor who takes the other side of the trade. Said differently, for every buyer there needs to be a seller, and vice versa. Although the theoretical literature predicts rational arbitrageurs with "deep pockets" to behave counter-cyclically, empirical studies have failed to identify them.

The closest paper to this one is Abbassi et al. (2016), which shows that banks with trading expertise increased their holdings of debt securities with falling prices during the crisis relatively more than banks without trading expertise. In contrast to their paper, I distinguish the investment behavior of the entire banking sector to non-bank financial institutions, i.e. the investment fund industry and the insurance company and pension fund sector.

In addition, their analysis only sheds light on the relative investment behavior of trading banks versus non-trading banks, but remains silent about whether these institutions *actually* buy when prices fall. In contrast to Abbassi et al. (2016), I show not only whether certain sectors act relatively *more* counter-cyclically than do others, but also that insurance companies and pension funds *actually* buy securities when prices fall and sell securities when prices rise. In addition, instead of concentrating only on times of stress, I aim to generalize the cyclical investment behavior across time periods, verifying that it is robust during the crisis. While periods of high stress are certainly crucial for financial stability, normal periods are also important to consider as these are times when systemic risk builds up.[4]

Security holdings of banks have received much attention recently.[5] However,

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[3] I am not the first who uses the term in this context. Weill (2007) shows theoretically that market makers are "leaning against the wind" by providing liquidity in times of market stress.

[4] Cella et al. (2013) show for the equity market that investors with short trading horizons sell more stocks in times of stress than investors with long trading horizons. Since banks' security portfolio consists mainly of debt securities, Cella et al. (2013) do not shed light on the investment behavior of banks. In addition, Cella et al. (2013) analyze the time series dimension rather than focusing on the within-time heterogeneity across securities.

[5] See e.g. Acharya et al. (2014), Acharya and Steffen (2015), Battistini et al. (2014), Gennaioli et al. (2014) and references therein.

there is little evidence on their trading behavior at the micro-level due to a lack of security-level holdings data. Micro-level evidence is crucial due to the heterogeneity in price dynamics of bonds depending on their security-level characteristics, such as the country and sector of issue, the maturity, or the credit rating.[6] In addition to showing that the banking sector as a whole acts pro-cyclically, I also exploit cross-sectional variation and show that the pro-cyclical behavior is stronger for banks that are relatively less capitalized. These results are consistent with models of limits to arbitrage due to capital constraints (Gromb and Vayanos, 2002; Shleifer and Vishny, 1997). However, it is at odds with Hanson et al. (2015) who model banks as patient fixed-income investors.

This paper also contributes to the investment fund literature. Fund managers may act with a short-term horizon due to agency frictions as they are exposed to injections and redemptions from investors (Chevalier and Ellison, 1997; Morris and Shin, 2015; Chen et al., 2010; Goldstein et al., 2015). While most papers focus on the relationship between performance and inflows, I investigate the investment behavior of investment funds. Many investment funds are measured on monthly or quarterly performance, which adds pressure to chase the market higher as it moves. Since fund managers may not be able to coordinate their selling behavior and have an incentive to time the market, it may be rational for them to trade pro-cyclically (Abreu and Brunnermeier, 2003). Consistent with this prediction, I provide empirical evidence that investment funds respond pro-cyclically to price changes. I also show that investment funds that face more outflows act relatively more pro-cyclically relative to other investment funds. Brunnermeier and Nagel (2004) similarly show that hedge funds that were not riding the tech bubble underperformed and suffered significant investor redemptions. Consistent with my results Giannetti and Kahraman (2017) find that closed-end funds trade more against mispricing in equity markets than open-end funds. My findings are also in line with the findings of Feroli et al. (2014) who show that a feedback loop between prices and sales of investment funds managers can emerge.[7] Since the

[6] Again, a notable exception that uses security-level holdings data is Abbassi et al. (2016). While they do not show how the whole banking sector responds to price changes, my findings show that banks generally respond pro-cyclically to price changes.

[7] In addition, Coval and Stafford (2007) and Shek et al. (2015) show that investment funds sell more when they face outflows. Raddatz and Schmukler (2012) also show that mutual funds' investment behavior tends to be pro-cyclical and thus not stabilizing; they reduce their exposure to countries in bad times and increase it during good times.

pro-cyclicality seems to be existent in both upswings and downturns, delegated portfolio managers may generally increase market volatility and distort asset prices (Guerrieri and Kondor, 2012).

In contrast to the pro-cyclical investment behavior of banks and investment funds, I find that insurance companies and pension funds act counter-cyclically with respect to price changes. While this is consistent with the view that long-term investors should stabilize the market by acting in a contrarian way, this has not been shown empirically.[8] Most studies even point to pro-cyclical behavior of insurance companies and pension funds. The reason for that may be that most studies focus on how credit ratings affect the investment behavior of investment funds, and failing to specifically ask the question of whether they actually act pro or counter-cyclically (Ellul et al., 2011, 2015; Merrill et al., 2012). Becker and Ivashina (2015) show that insurance companies buy corporate bonds that are the highest yielding within each rating group as they are reluctant to hold more capital when they hold worse-rated bonds.[9] I find that counter-cyclical investment behavior is weaker in times when insurance companies' and pension funds' negative duration gap is larger. This suggests that a low interest rate environment may weaken the counter-cyclical behavior as it can result in larger duration gaps for insurance companies and pension funds. In addition, I present evidence that insurance companies and pension funds buy bonds whose excess bond yields rise. This supports the hypothesis that they are buy-and-hold investors and not averse to liquidity risk. In general, my results suggest that the investment behavior of insurance companies and pension funds can be a stabilizing force on the capital markets.

My results are consistent with intermediary asset pricing models. While in standard asset pricing models, households are the marginal investors and determine asset prices, see e.g. Campbell and Cochrane (1999), my results suggest that financial intermediaries can have asset pricing effects. My results are therefore consistent with frameworks where the marginal investors are financial intermediaries (Adrian and Boyarchenko, 2012; Brunnermeier and Pedersen, 2009; He and Krishnamurthy, 2013). These models have been, for example, tested by Adrian et al.

[8] My findings are consistent with an asset insulator model like in Chodorow-Reich et al. (2016). They show that usually stock prices of insurance companies do not drop when they suffer losses on their security holdings.

[9] Other studies that indicate that insurance companies and pension funds act pro-cyclically are Acharya and Morales (2015); Domanski et al. (2017); Duijm and Steins Bisschop (2015); Haldane (2014).

(2011) and Adrian et al. (2010a).

However, my results also suggest that direct empirical tests of intermediary asset pricing models should not only take into account financial constraints of broker dealers but also of other financial intermediaries, such as investment funds and insurance companies and pension funds. For these institutions it is important that it is not necessarily the leverage ratio that determines asset prices. My results suggest that net outflows of investment funds and the duration mismatch of insurance companies and pension funds are potential risk factors that can be used for testing intermediary asset pricing models.

My results are also consistent with leverage cycle theories in the spirit of Adrian and Shin (2010, 2014). In particular, my finding that banks act pro-cyclically and even more so when they are more capital constrained is in line with these leverage cycle theories. When banks suffer losses on their security holdings, this tightens their constraints and induces them to sell securities whose prices have fallen. This investment behavior can again have an impact on prices and therefore their constraints.[10]

Lastly, my results are also consistent with models of limits to arbitrage due to capital constraints (Gromb and Vayanos, 2002; Shleifer and Vishny, 1997) and theories where banks are acting pro-cyclically (Hanson and Stein, 2015; Shleifer and Vishny, 2010). In contrast, my results are at odds with models where banks are risk absorbers, see for example Hanson et al. (2015), where banks are modelled as patient fixed-income investors.[11] My findings are also inconsistent with theories that model less levered institutions as stabilizing (Shleifer and Vishny, 1992). I find that that less levered institutions do not necessarily act as a stabilizing force. While even non-levered institutions such as mutual funds can exacerbate price dynamics and amplify financial cycle dynamics, insurance companies and pension funds act in a stabilizing fashion.

[10] The framework by Geanakoplos (2010) is also consistent with my findings.

[11] However, one difference to Hanson et al. (2015) is that they focus on the holdings of securities by financial institutions while I investigate their trading behavior.

2.2 Data

2.2.1 Data Description

The Microdatabase Securities Holding Statistics of the Deutsche Bundesbank's Research Data and Service Centre of the Deutsche Bundesbank provides quarterly security-by-security-level holdings data of all investors based in Germany from 2005 Q4 onwards. The data includes the raw, nominal and market value of each security. The institutions report the raw value of the security holdings to the Deutsche Bundesbank, which subsequently calculates the nominal and market value. The raw value is the nominal value held in the currency of denomination. The nominal value is the notional amount of security holdings and does not reflect price movements. The market value is the number of securities held multiplied by the price.[12] The price that is used to calculate the market value of the security is gathered from the Centralised Securities Database (CSDB) and reflects the market price of the security at the end of the quarter. I use this price for the rest of my analysis. ΔPrice is calculated by taking the difference of the log of the price.

The security is identified with the International Security Identification Number (ISIN). Information about the currency of denomination, the security classification and the issuing sector of the security is also available. The holdings are further split up by the sector that is holding the security. The largest holding sectors are banks, investment funds and insurance companies and pension funds, followed by non-financial corporates and households. While this dataset contains information about the sector that is holding the security, it does not specify which institution within the sector is holding it.

However, I also use the institution-level security-level holdings data and balance sheet information for all banks in Germany for the same time period from the Microdatabase Securities Holding Statistics and the monthly bank balance sheet statistics, respectively. For investment funds, I use institution-level security-holdings data and balance sheet data from the investment fund statistics of the Deutsche Bundesbank. However, the institution-level security-holdings data is only available from the end of 2009. For insurance companies and pension funds the institution-level security-holdings data is not available. For a detailed data description of the Microdatabase Securities Holding Statistic see Amann et al. (2012)

[12]The nominal value needs to be adjusted to reflect only investment decisions (see Appendix).

and Bade et al. (2016).

In order to harmonize the analysis for all three sectors, I use sector-level data for my main analysis. In addition, I only consider the three largest sectors: banks; investment funds; and insurance companies and pension funds. I also restrict my analysis to debt securities and discard any equity security holdings.

I download additional security-specific characteristics from Bloomberg and Datastream. The yield refers to the yield-to-maturity. The credit rating is the S&P rating if available and the Fitch rating otherwise. Investment grade rating is defined as a rating better than BB+. For parts of the analysis, the data provided by the Deutsche Bundesbank is merged with publicly available data. The country-specific 10-year generic government bond yield, the consumer price index and GDP are from the IMF. I obtain GDP growth and the inflation rate by taking the natural log change of GDP and the consumer price index. If GDP is not available quarterly, I interpolate the annual value linearly. The VIX is the log of the implied volatility for S&P 500 stock options and is obtained from the Chicago Board Options Exchange and downloaded through Datastream. The EONIA is from the ECB. The country-specific variables are merged with the first two characters of the ISIN code. This is consistent with the nationality and not the residence principle and accounts for offshore issuance of securities.

2.2.2 Summary Statistics and Stylized Facts

Table 2.1 shows the summary statistics of the main variables. The average value of a security held is 22.6 million Euros for insurance companies and pension funds, 31.8 million Euros for investment funds and 57.6 million for banks. Insurance companies and pension funds, which hold a significantly smaller quantity of securities, are the smallest group of debt security holders among the three sectors. Insurance companies and pension funds not only hold fewer securities, but they also trade less. However, when they do trade, they transact larger volumes than do investment funds. Investment funds are the most active traders among the three; the number of observations for buy and sell outstrip those for banks and insurance companies and pension funds. On average, the amounts they trade are smaller than those of banks and insurance companies and pension funds. This is also true for the percentage changes in their holdings. When investment funds trade, they increase their holdings on average by 22 percent and reduce their holdings on average by 21 percent. The numbers for banks and insurance companies and pension funds are larger. Banks increase their holdings on average by 37 percent and reduce their holdings by 41 percent. Insurance companies and pension funds change their holdings on average by 31 percent. The standard deviation of the netbuy variable also suggests that investment funds transact smaller amounts than do banks and insurance companies and pension funds. The standard deviation is 43 percent for for investment funds compared to 67 percent for insurance companies and pension funds and 81 percent for banks. Lastly, while the average price change is close to zero, the standard deviation of the price change is 4 percent.

Figure 2.1, Figure 2.2 and Figure 2.3 show the holdings of debt securities of the three sectors over time. Banks are the largest holder of debt securities, followed by investment funds and insurance companies and pension funds. While banks increased their security holdings before the beginning of the financial crisis, they have since reduced their security holdings significantly (Figure 2.1). In contrast, non-bank financial institutions such as investment funds and insurance companies gained more importance in the provision of market-based funding. Although investment funds built up their security holdings over time they were selling securities during the sovereign debt crisis (Figure 2.2). In contrast, insurance companies and pension funds were building up debt securities even between 2010 and 2012 (Figure 2.3).[13]

The active selling behavior of banks and investment funds in the crisis paid off in the short run, as can be seen from Figure 2.4. The capital gains on their debt security portfolios were positive before dropping into negative territory in mid-2010, but still without major losses. Insurance companies and pension funds, however, suffered severely when their bonds fell in value during the crisis, but their medium-term strategy paid off when prices began to recover. Between mid-2011 and the end of 2014 capital gains on their debt securities have been nearly 30 percent. They have outperformed banks and investment funds not only since mid-2010, but also since the beginning of the financial crisis. While insurance companies and pension funds kept buying securities during the crisis, temporarily suffering losses, they outperformed the other two sectors in the medium run. This is in line with the statement by Matteo Renzi, at that time Italy's prime minister, to the Italian Senate on February 17, 2016:

> "Let me say that if some northern European lenders had kept their

[13]For the portfolio composition of the three sectors see Table 2.17.

Italian government debt in 2011-2012, they would be earning much more."

However, holding or even increasing the holdings of securities that have performed poorly can be a risky strategy as bond prices tend to continue their trend for several quarters before price trends reverse (Cutler et al., 1991, 1990; Moskowitz et al., 2012). Although the selling behavior that Matteo Renzi stresses has been formally rationalized by DeLong et al. (1990b), not every investor can take the same side of a trade. Due to the adding-up constraint, someone has to buy the securities when their prices fall and others are selling them.[14] The above results suggest that insurance companies and pension funds have been the institutions that tried to "catch the falling knife". However, these stylized facts only show simple aggregated numbers that can be influenced by other factors. In the next section I turn to a security-by-security analysis to test the systematic investment behavior of the different sectors more formally.

2.3 Main Results

I attempt to shed light on the question of which institutions act pro-cyclically or counter-cyclically by investigating how their investment decisions depend on price changes. My regression is in the spirit of Abbassi et al. (2016), but instead of comparing trading banks to non-trading banks, I compare insurance companies and pension funds to banks and investment funds. I treat insurance companies and pension funds as my benchmark and define a dummy *Banks* that equals one for banks and zero otherwise. The second dummy *Funds* takes a value of one for investment funds and zero otherwise. I regress the percentage increase in the nominal amount held by each institution on the interaction of the respective dummies with the price changes. The coefficients on the interaction terms show how much more pro-cyclically banks and investment funds act compared to insurance companies and pension funds. I estimate the following specification:

$$Netbuy_{i,s,t} = \beta_1 \Delta Price_{s,t-1} * Funds_i + \beta_2 \Delta Price_{s,t-1} * Banks_i + \alpha_{s,t} + \alpha_{i,t} + \alpha_{i,s} + \epsilon_{i,s,t} \tag{2.1}$$

The results are shown in column (6) of Table 2.2. Netbuy is the change in the

[14] DeLong et al. (1990b) call them "passive investors".

log of the nominal amount held of security s at quarter t given the institution trades.[15] ΔPrice is the change of the log price of the security.[16] The price change at time t reflects the change in the price from the end of quarter $t-1$ until the end of quarter t. I lag ΔPrice by one quarter in order prevent contamination of my results by the possibility that trading decisions have a price impact.[17] In addition, this allows me to rule out the possibility that trading decisions are executed before the institution observes the reported price.[18]

In this specification I also include security∗time, sector∗time and security∗sector fixed effects. The inclusion of security∗time fixed effects controls for all time-variant and time-invariant security-specific characteristics so that a separate security fixed effect is spanned by the security∗time fixed effect. This specification allows me to draw conclusions about the investment behavior in one specific security at a given point in time. For instance, a positive correlation between the error term and the change in the price leads to an overestimation of the price change coefficient. Comparing banks and investment funds to insurance companies and pension funds allows me to control for unobserved and observed time-varying security characteristics. The additional inclusion of sector∗time fixed effects controls for time-variant and time-invariant sector-specific characteristics. By controlling for sector∗time fixed effects, I can confirm that results hold if I control for the amount invested by the specific sector at a given time. Lastly, I saturate the specification with security∗sector fixed effects to control for observed and unobserved preference of the three sectors for specific securities.

Column (6) shows that both banks and investment funds invest more procyclically in response to price changes than do insurance companies and pension

[15]The netbuy measure reflects only buy and sell decisions and no valuation effects. The results are robust to the use of other netbuy measures. For instance, the results do not change qualitatively whether I use the log of the amount bought minus the log of the amount sold or the amount in Euros. The results are also robust when I use buy and sell separately instead of using a netbuy measure. The results are also robust when hold decisions are included.

[16]The results are robust to the inclusion of higher lags of the price change as well as price changes of a lower frequency.

[17]In this case the change in the price and the decision to buy or sell may be jointly determined.

[18]If I included the contemporaneous price change, trading decision could have been executed any time during the quarter t, although the price change I am using in my regression has not been observed as it is the price change from the end of quarter $t-1$ until the end of quarter t. Therefore, unless the trading decision is always executed at the last point of the quarter, the contemporaneous independent variables may be observed only after the decision to transact is taken.

funds (Table 2.2). A 10 percent price increase of a security is associated with a 8.6 percentage point stronger increase by banks and a 4.3 percentage point stronger increase of the nominal position by investment funds relative to insurance companies and pension funds. As can already be seen from the interpretation of the results, the disadvantage of including security∗time fixed effects is that I can only make statements about whether the sectors trade more or less pro or counter-cyclically to price changes relative to insurance companies and pension funds and not whether they actually buy or sell.

Columns (1)-(3) exclude the security∗time fixed effects. Excluding security∗time from the specification relaxes the restrictions that at least two sectors need to trade the security at a given point in time. The exclusion of the security∗time fixed effect implies that the level of the price change is identified as it is no longer collinear with the fixed effects. The interpretation of the level of the price change coefficient is the response of insurance companies and pension funds to price changes. Column (3) of Table 2.2 shows that a 10 percent increase in the price is associated with a 4.3 percent decrease of the nominal amount held by insurance companies and pension funds. The interaction of the price change with the dummy *Funds* shows that investment funds increase their nominal holdings by 5.7 percentage points percentage more, i.e. they increase their holdings by 1.4 percent. The interaction of the price change with the dummy *Banks* shows that banks increase their holdings by 7.9 percentage points more than insurance companies and pension funds, i.e. they increase their holdings by 3.6 percent. Column (2) and (3) are equivalent to splitting the sample and estimating the equation separately for banks, investment funds and insurance companies and pension funds. This also allows testing the null hypothesis whether institutions do not respond to price change against the alternative hypothesis that they change their holdings in response to price changes. This is in contrast to Table 2.2 where I test whether institutions change their holdings differentially in response to price changes.

Therefore, the following specification can be estimated:

$$Netbuy^{X}_{s,t} = \beta_1 \Delta Price_{s,t-1} + \alpha_s + \alpha_t + \epsilon_{s,t} \tag{2.2}$$

X represents investment funds, banks or insurance companies and pension funds. Columns (1) and (2) show the results for when X equals investment funds; columns (2) and (3) are for insurance companies and pension funds; columns (5) and (6) show the results for banks. Again, α_s is a security fixed effect that controls for security-specific characteristics that are time-invariant. The inclusion of security fixed effects controls for the fact that different securities have different time-invariant characteristics, such as the expiration date or the coupon. It also enables me to analyze the investment behavior in a specific security over time, which circumvents the issue that the number of securities outstanding in the economy can change.[19] α_t is a time fixed effect that controls for market-wide development. As I split the equation into three parts the security fixed effect as well as the time fixed effects are sector-specific. This is equivalent to the sector$*$time and sector$*$security fixed effect in Table 2.2.

Table 2.3 shows the estimation of equation (2) sector by sector. Investment funds and banks buy securities whose prices have risen and sell securities that have lost value, i.e. they have an upward sloping demand curve. In contrast, insurance companies and pension funds buy when prices have fallen and sell when prices have risen.[20] The inclusion of time fixed effects implies that aggregate time-specific characteristics that affect the investment behavior are discarded. For instance, when banks sell securities when prices fall, if this is also the time when their funding dries up or they have to de-lever, this would not capture pro-cyclical behavior due to the time fixed effects. On the other side, when insurance companies and pension funds increase their holdings in general in times when prices fall, this would not be captured in a specification with time fixed effects. Including time fixed effects might somewhat overcontrol some of the effects. Instead of showing how much insurance companies and pension funds actually buy when prices fall, it rather shows how much is bought of securities whose prices decreased relatively more than those of other securities.

Therefore, Table 2.3 also shows the results without time fixed effects. The effects are again statistically and economically highly significant. A two standard deviation increase in the price (7.4 percent) is associated with 2.52 percent increase in the nominal holdings for banks, 0.78 percent for investment funds and a 6.29 percent decrease for insurance companies and pension funds. These magnitudes add up to an increase of 1.45 million Euros for banks, 0.25 million for investment funds and 1.42 million decrease for insurance companies and pension funds.[21]

[19]See appendix for details.

[20]In the working paper version of the paper I show the response of the various institutions to macro-financial variables, see Timmer (2016).

[21]It is important to stress that these numbers are for a single security. Given that the institutions

The counter-cyclical investment behavior of insurance companies and pension funds offsets almost completely the pro-cyclical investment behavior of banks and investment funds, although the security holdings of banks and investment funds are significantly larger than those of insurance companies and pension funds.

The results above indicate that banks and investment funds act like positive feedback investors who “buy securities when prices rise and sell when prices fall" (DeLong et al., 1990b). Since insurance companies and pension funds have “deep pockets" they may be able to trade against them (DeLong et al., 1990a).[22] The investment behavior of banks and investment funds might be rational for several reasons. In the next section, I empirically investigate one potential channel that could generate these findings, a balance sheet channel.

2.4 Balance Sheet Constraints

2.4.1 Balance Sheets and Investment Behavior

The pro-cyclical investment behavior of banks and investment funds could be explained by their unstable balance sheet composition. I test this channel by exploiting cross-sectional heterogeneity within the banking and investment fund sector. This within-sector heterogeneity confirms that institutions with tighter constraints act in a more pro-cyclical way to price changes. In particular, banks with tighter capital constraints and investment funds with more outflows act relatively more pro-cyclically. The constraints of banks and investment funds also tighten when the institutions suffer losses on their security holdings. Since price changes exhibit a momentum factor at short horizons and banks and investment funds are averse to short-term losses, the pro-cyclical investment behavior of banks and investment funds may be rational.

In contrast, insurance companies and pension funds have long-term liabilities so that they are not exposed to redemption pressure. While insurance companies and pension funds act relatively less counter-cyclically in times when their negative duration gap rises, the duration gap does not seem to be related to losses on their

hold several thousands of securities, the results sum up to even larger aggregate numbers.

[22]Insurance companies’ and pension funds’ investment behavior is consistent with passive investors in DeLong et al. (1990b).

security holdings.[23] The benefit of a more stable balance sheet may explain why insurance companies and pension funds are acting in a counter-cyclical manner and can benefit from buying securities whose values have fallen.

Before I empirically link the institution's balance sheet constraints to their investment behavior, I lay out the balance sheet structure of the institutions under investigation and discuss the balance sheet channel hypothesis in greater detail.[24]

2.4.1.1 Banks

Figure 2.5 shows different categories of the aggregated balance sheet of German banks proportionally. The total size of the balance sheets amounted to 7.85 trillion Euros in 2014, which is around 270 percent of Germany's GDP (2.9 trillion Euros in 2014). The liability side mainly consists of retail and wholesale deposits. Only 382 billion Euros, approximately 5 percent, are equity capital. Both retail and interbank borrowing are short-term liabilities that can be withdrawn without an extended period of notice.[25]

When creditors refuse to roll over their debt or actively withdraw their funds, the asset side needs to be reduced in order to service the liabilities. The asset side of banks mainly consists of longer-term assets, such as debt securities and loans. When funding liquidity dries up, banks start by reducing their most liquid assets, such as cash and excess reserves at the central bank. As these contribute only a small amount to the aggregate balance sheet and banks are unable to call in loans, debt securities need to be sold. If the liquidity dryup is systemic and non-specific to a single bank, banks may have trouble finding a buyer for the securities, forcing them to sell them below their fundamental value, what is known as a "fire sale".

The small amount of equity capital exacerbates their unstable balance sheet structure. The poorer capitalized a bank is, the more leverage increases when the value of the assets declines. In order to keep leverage constant, banks need to sell securities which can lead to a spiral between lower asset prices and weaker

[23]Chodorow-Reich et al. (2016) show that stock prices of insurance companies in the US are usually not sensitive to losses on their security holdings.

[24]See also Hanson et al. (2015) for a discussion of the balance sheets of various financial intermediaries.

[25]While in the banking crisis as described in Diamond and Dybvig (1983) retail deposits were withdrawn, the most recent financial crisis was characterized by a withdrawal of wholesale funding and money market fund shares.

balance sheets (Adrian and Shin, 2010, 2014; Brunnermeier, 2009; Brunnermeier and Pedersen, 2009; Greenwood et al., 2015).[26]

The ability of banks to take on additional exposure is therefore limited by their capital cushion (Danielsson et al., 2012). In particular, a better capitalized bank may be able to act in a counter-cyclical fashion, a strategy that pays off only at longer horizons, as it is relatively less sensitive to losses on their security holdings in the short run.[27] In contrast, a bank with a lower capital ratio is more sensitive to losses on their securities. Therefore, it may be rational for these banks to act pro-cyclically, as this is a relatively less risky strategy due to the short-term momentum component of bond prices.[28] In order to shed light on the question of whether a balance sheet channel is actually at work, I test whether there is heterogeneity in the cyclical investment behavior across banks depending on their degree of capitalization.

> **Hypothesis 1:** Banks with tighter capital constraints act relatively more pro-cyclically.

In order to test **Hypothesis 1**, I obtain data on bank-level security holdings. The dataset covers every bank in Germany and their security holdings from 2005 Q4 through 2014 Q4. For all 1954 banks in my sample I define the capital ratio of the bank as the ratio of equity to total assets. I fix the capital ratio at the beginning of the sample to assure that changes in the capital ratio are not driven by active balance sheet management, see e.g. Adrian and Shin (2010).[29] The empirical

[26]This is not only the case for banks that mark-to-market. Geanakoplos (2003) and Fostel and Geanakoplos (2008) stress the importance of collateral constraints for balance sheet dynamics. For instance, a higher levered bank is more sensitive to price changes as it alters the collateral value a bank can borrow against. This is independent whether the bank marks-to-market their security holdings. In addition, lower capitalized banks are more vulnerable as they mechanically have a larger share of unstable funding. Adrian et al. (2015) also point out that accounting rules are unlikely the reason for balance sheet dynamics. Laux and Leuz (2010), Allen and Carletti (2008) and Plantin et al. (2008) describe the mark-to-market behavior of banks in more detail.

[27]See Abbassi et al. (2016).

[28]While I pose the assumption here that pro-cyclical investment behavior is relatively less risky at short horizons than counter-cyclical investment behavior, I test this more formally in section 5.

[29]In this regression, I am only interested in the cross-sectional variation of the cyclical investment behavior across banks. If I used the contemporaneous capital ratio instead, the coefficient could be driven by both changes in the capital ratio over time and the cross-sectional component. The capital is the book value and not the market value of equity.

strategy uses the bank's capital ratio and interacts it with the price change of the security. I expect a negative coefficient for the interaction term of the price change with the capitalization measure, i.e. poorer capitalized banks act relatively more pro-cyclically.

The empirical specification for column (4) in Table 2.4 is as follows:

$$Netbuy_{i,s,t} = \beta_1 \Delta Price_{s,t-1} * Capital_i + \alpha_{s,t} + \alpha_{i,t} + \epsilon_{i,s,t} \tag{2.3}$$

This is the most conservative specification and includes security∗time fixed effects and institution∗time fixed effects. This allows me to control for all unobserved time-varying institution and security-specific characteristics. The separate inclusion of security fixed effects, time fixed effects and institution fixed effects is not possible as they are spanned by the inclusion of security∗time and institution∗time fixed effects. In addition, the inclusion of the level of the price change and the capital ratio is not possible due to collinearity with the fixed effects. Standard errors are double clustered at the security and institution-level to account for serial correlation between observations of the same security and institution across time.[30]

Table 2.4 shows that the coefficient of the interaction between the price change and the capital ratio is negative and statistically significant. A one percentage point lower capital ratio is associated with a 3.1 percentage point more pro-cyclical investment behavior for a 10 percent price change. This result provides evidence in support of **Hypothesis 1**. Since the price change is collinear with the security∗time fixed effect, the price change coefficient is not identified in equation (3). Columns (1)-(2) relax this restriction so that the level of the price change can be included in the regression specification. The results also hold when I exclude institution∗time fixed effects and security∗time fixed effects. For instance, column (2) shows the specification with security and institution∗time fixed effects separately. Since the capital ratio is demeaned by the sample average, the level coefficient can be interpreted as a response of a bank with an average capital ratio, which is approximately 5 percent. A bank with a capital ratio of 5 percent increases the nominal holdings by 6.5 percent in response to a 10 percent price increase. For every one percentage point lower capital ratio, the response is 2.5 percentage points stronger. For instance, a bank with a capital ratio of 4 percent increases its holdings by 9 percent instead of 6.5 percent.

[30]The results are even stronger when I cluster either on the security, on the institution or on the security-institution level. The results also hold when I include security∗institution fixed effects.

Table 2.5 splits the sample into a pre-crisis, crisis, post-crisis, and a post-regulatory reform implementation period. This follows the difference-in-difference approach in Adrian et al. (2017), who investigate the impact of dealer balance sheets on bond liquidity provision and show that while bonds traded by more levered institutions have been more liquid prior to the crisis, this relation reverses post-crisis. The impact of the capital ratio on the cyclical investment behavior should become stronger when overall constraints are tighter if a causal mechanism between the tightness of the capital constraint and the pro-cyclical investment behavior is at work. When banks' capital ratios rise, they are pushed away from their financial constraint, which should weaken the impact of the capital ratio on the pro-cyclical investment behavior.

Table 2.5 indeed shows that the coefficient is strongest in the crisis period when banks suffered losses and capital constraints became tighter. The impact is also negative in the pre-crisis period, at the peak of the leverage cycle, when capital constraints were close to being binding. When security prices started to recover after Draghi's announcement to do "whatever it takes to preserve the Euro" capital positions of banks improved again. This distanced banks from their financial constraint, which arguably led to the weakening of the impact of capital ratios on the pro-cyclical investment behavior in the post-crisis period.[31] Lastly, in 2014 new capital requirement for banks were introduced (European Commission, 2013). The results show that the impact of the capital ratio on the pro-cyclical investment behavior is weakest in the post-regulatory reform implementation period and if anything, the relation reversed. This result suggests that that the implementation of regulatory reforms had a mitigating effect on the pro-cyclical investment behavior of banks.[32]

2.4.1.2 Investment Funds

The investment fund industry in Germany is a significant sector, with an aggregate balance sheet of 1.7 trillion Euros in 2014 (more than 50 percent of Germany's GDP). In Germany, the sector consists almost exclusively of open-end mutual funds, such

[31]See Acharya et al. (2017) for the real effects of the "whatever it takes" announcement.

[32]Note that in this table the price coefficient as well as the capital coefficient are absorbed by the security∗time fixed effect as well as the institution∗time fixed effect, respectively.

as bond and mixed funds.[33] The leverage of these investment funds is limited. Figure 2.6 shows that only 2 percent of their liability side consists of loans. At first glance, the fact that investment funds are not vulnerable to runs on their debt liabilities may raise doubts about their contribution to systemic risk. As their investors provide equity capital, this suggests that investment funds can be seen as benign with respect to financial stability.

However, investors in open-end mutual funds can draw down their capital quickly. This changes the assets under management of the fund, which is the fund's equity capital. In other words, investment funds' capital is not permanent, unlike the equity capital of non-financial corporations. As investment fund shares issued make up the lion's share of investment funds' liabilities, simple metrics like the total assets to equity ratio can lead to misleading conclusions when it comes to identifying financial vulnerabilities. Once investors start redeeming assets, a feedback loop between redemptions by investors and sales of portfolio managers can emerge, as the redemptions of investors are usually not orthogonal to the performance of the investment fund.[34] In particular, losses on security holdings are associated with investor redemptions; since investment funds are averse to redemptions from investors, they may have incentives to limit short-term losses. This is particularly strong when investment funds already suffered outflows, as higher outflows make them more vulnerable to falling prices.[35] From this the following hypothesis arises:

> **Hypothesis 2:** Investment funds with more net outflows act relatively more pro-cyclically.

In order to test **Hypothesis 2**, I use data on all investment funds and their security-level holdings. However, in contrast to the bank-level security-level holdings data, the data on investment funds is only available from 2009 Q4 onwards.

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[33] In 2014 there have been 5,923 investment funds in Germany of which 57.2 percent are mixed mutual funds and 15 percent are bond mutual funds. Only 0.5 percent are hedge funds.

[34] See e.g. Chevalier and Ellison (1997) and Chen et al. (2010) for the relationship between fund outflows and performance.

[35] See also Goldstein et al. (2015), Feroli et al. (2014) and Morris and Shin (2015) for empirical and theoretical evidence on this channel.

First, I define the net outflow of a fund as

$$NetOutflow_{i,t} = -(\frac{Shares_{i,t} - Shares_{i,t-1}}{NAV_{i,t-1}}) \tag{2.4}$$

Shares are the investment fund's shares outstanding at face value to control for outflows to be driven mechanically by the price of the investment fund. NAV is the net asset value, used to scale for how large the outflows are relative to the size of the investment fund.

I estimate the following specification to test whether investment funds that suffered more outflows indeed rebalance their portfolio towards securities that have been risen versus those that have been fallen:

$$Netbuy_{i,s,t} = \beta_1 \Delta Price_{s,t-1} * NetOutflow_{i,t-1} + \alpha_{s,t} + \alpha_{i,t} + \epsilon_{i,s,t} \tag{2.5}$$

Column (4) of Table 2.6 shows the results with double clustered standard errors at the security and institution-level to account for serial correlation between observations of the same security and institution across time.[36] A 10 percent net outflow is associated with a 1.8 percentage point stronger pro-cyclical investment behavior for a 10 percent price change.

2.4.1.3 Insurance Companies and Pension Funds

The total size of the insurance companies' and pension funds' balance sheet in Germany in 2014 was 2.4 trillion Euros (more than 80 percent of Germany's GDP). On the asset side, cash and deposit holdings are much larger than for banks and contribute 21 percent to total assets, while almost 60 percent are securities (Figure 2.7). The leverage ratio of insurance companies is much smaller compared to banks. The lion's share of liabilities is represented by insurance technical reserves; these are net equity of households in life insurance and pension fund reserves or prepayments of insurance premiums and reserves for outstanding claims. These long-term liabilities are mostly contingent and their payouts are relatively independent of the state of the real economy and overall financial conditions. This predictable liability structure may give insurance companies and pension funds more autonomy in their portfolio choice as compared to banks or investment funds. For instance, an accident with an insured car, a damage to an insured building or a

[36] The results are even stronger when I cluster either on the security, on the institution or on the security-institution level. The results also hold when I include security∗institution fixed effects.

death of a person are events that could be covered by insurance companies and cause payouts. As the structure of the liability side of insurance companies' and pension funds' balance sheet is relatively persistent, this keeps their funding and rollover risk relatively moderate and leaves them with more "skin in the game".[37] In addition, insurance companies and pension funds in Germany do not have to mark-to-market their security holdings during my sample period (Fabozzi, 2012).[38] This may enable "deep pocket investors", such as insurance companies and pension funds, to buy securities when prices have dropped when other actors, such as banks and investment funds, may sell these securities. When prices have decreased, insurance companies and pension funds can benefit from a reversal of the price if they hold on to the security. Therefore, insurance companies and pension funds may act counter-cyclically due to their more stable balance sheet as compared to those of banks and investment funds.

However, while insurance companies and pension funds are less sensitive to losses on their security holdings than banks and investment funds, they are unlikely to be totally unconstrained investors. While their long-term liabilities relative to their assets are usually an advantage, the duration mismatch of assets and liabilities can also become problematic. Insurance companies and pension funds discount their liabilities with the risk-free rate. When the risk-free rate falls, insurance companies' and pension funds' liabilities increase relatively more than their assets due to their negative duration gap. In order to prevent having a duration mismatch that is too large, insurance companies and pension funds may engage in duration matching by buying long-term bonds, independent of the price change. While it is usually the case that insurance companies and pension funds buy securities whose value dropped most, this may change when the duration mismatch increases. When interest rates fall, the prices of long-term bonds rise and the duration mismatch of insurance companies and pension funds increases. In order to investigate whether the duration mismatch is indeed a balance sheet constraint that affects the investment behavior of insurance companies and pension funds, I test the following hypothesis:

[37] Acharya et al. (2011) discuss the systemic importance of insurance companies for the global economy in more detail. Manconi et al. (2016) document their selling behavior when they face a large outflow.

[38] With the introduction of Solvency II in January 2016, insurance companies and pension have to mark-to-market their security holdings.

Hypothesis 3: Insurance companies and pension funds act relatively less counter-cyclically when their duration mismatch increases.

Security holdings data is not available on the institution-level for insurance companies and pension funds. In order to test the hypothesis, I instead use balance sheet data for the insurance company and pension fund sector in Germany provided by the Deutsche Bundesbank and proxy the duration mismatch by constructing a maturity mismatch measure by dividing insurance companies' and pension funds' long-term liabilities by their long-term assets. A higher ratio of long-term liabilities to long-term assets is associated with a higher on-balance sheet maturity mismatch. Since the duration of an asset is closely linked to its maturity, the maturity mismatch can be seen as a proxy for the duration mismatch.[39]

In order to test this hypothesis, I estimate the following specification:

$$Netbuy_{s,t} = \beta_1 \Delta Price_{s,t-1} + \beta_2 \Delta Mismatch_{t-1} * \Delta Price_{s,t-1} + \alpha_t + \alpha_s + \epsilon_{s,t} \quad (2.6)$$

The results are shown in column (2) of Table 2.7. The specification includes security fixed effects to control for time-invariant security-specific characteristics. Time fixed effects control for observed and unobserved time-specific characteristics. As this regression is on the sector-level, all sector-specific time trends are also controlled for. If **Hypothesis 3** is true, I would expect a positive sign for the interaction of the change in the maturity mismatch and the change in the price. The larger the mismatch, the more pro-cyclically (less counter-cyclically) insurance companies and pension funds act on the capital markets with respect to price changes.[40]

Column (2) of Table 2.7 shows that a one percentage point increase in the mismatch ratio is indeed associated with a 3.5 percentage point weaker counter-cyclical investment behavior for a 10 percent price change. Column (1) shows that this pattern holds when time fixed effects are not included in the regression. In this case counter-cyclical investment behavior is even stronger as insurance companies and pension funds seem to buy more in general when prices fall. This also holds when I include macro-economic controls in the regression instead of using time

[39] Of course, insurance companies and pension funds can use interest swaps to hedge their interest rate exposure. However, since hedging is expensive, insurance companies and pension funds may not fully hedge their exposure.

[40] In recent work Domanski et al. (2017) provide a theoretical framework for this behavior. They also provide consistent evidence with aggregate data.

fixed effects, seen in column (4). Column (5) is the most conservative specification. In order to rule out that the duration mismatch is correlated with other macro-economic variables and that the mismatch only picks up this correlation, I control for the interaction between several macro-economic variables, such as German GDP growth, inflation, the 10-year government bond yield, the EONIA and the VIX and the price change. Even controlling for these other interaction terms, the interaction of the price change with the change mismatch ratio is still highly significant.
After having shown that insurance companies and pension funds act relatively less counter-cyclically in times when the duration mismatch increases, this still poses the question what drives the aggregate pattern of section 2, i.e. that insurance companies and pension funds act counter-cyclically on average. One mechanism that could explain these findings is the correlation of the tightness of their constraints with gains and losses on the portfolio holdings. In contrast to investment funds and banks, whose constraints tighten when they suffer losses on their security holdings, the duration mismatch of insurance companies and pension funds should, if anything, decrease when prices fall due to their negative duration gap.[41] Therefore, insurance companies and pension funds may use this comparative advantage to act counter-cyclically. I test the link between capital gains and the tightness of the balance sheet constraint more formally in the next section.

2.4.2 Balance Sheet Constraints and Capital Gains

The above hypotheses and results suggest that there is a link between capital gains and losses on their portfolio holdings of different investor types and the tightness of their constraints. As shown in the previous section, poorer capitalized banks and investment funds with more outflows act relatively more pro-cyclically. When insurance companies' and pension funds' duration mismatch increases, they also tend to act relatively less counter-cyclically.

In order to align the findings of section 2 with the overall pattern that insurance companies and pension act counter-cyclically and the banking and investment fund sector acts pro-cyclically, I test whether losses on portfolio holdings are affecting the constraints of the various institutions. When prices fall and losses on their security holdings lead to tighter constraints, institutions may (i) be forced to sell securities

[41]When interest rates fall and security prices rise, assets of insurance companies and pension funds may rise relatively less than their liabilities due to their larger sensitivity to interest rate changes.

or (ii) sell securities in order to avoid further price falls tightening constraints even more. This may be the case because pro-cyclical investment behavior is profitable in the short run. In order to test whether the tightness of the constraint is related to the losses on the security holdings, I estimate the following specification:

$$Constraint_t^X = \alpha + \beta_1 Netgains_{t-1} + \epsilon_t \tag{2.7}$$

where X is either (i) investment funds, (ii) banks or (iii) insurance companies and pension funds. For investment funds, I again use net outflows of a fund as defined in the last section as a constraint; for banks I use capital over total assets at the beginning of the sample and for insurance companies and pension funds I use the change in the maturity mismatch.[42] These simple correlations in column (1), (2) and (4) of Table 2.8 confirm that banks' and investment funds' constraints tighten when they suffer losses on their security holdings and insurance companies' and pension funds' constraints, if anything, loosen.

In order to test this correlation more structurally, I can use institution-level data for banks and investment funds to estimate the following equation:

$$Constraint_{i,t}^X = \beta_1 Netgains_{i,t-1} + \alpha_i + \alpha_t + \epsilon_{i,t} \tag{2.8}$$

where X can be either investment funds or banks. The specification includes institution fixed effects to control for unobserved and observed time-invariant heterogeneity in the cross-section of investment funds or banks, e.g. some banks may be structurally better capitalized than others. The specification also includes time fixed effects to control for institution-invariant time trends. The results from the simple correlation can be confirmed in columns (3) and (5) of Table 2.8. When banks suffer losses on their security holdings it tightens their constraints by reducing their capital. Losses on investment funds' balance sheets are associated with redemptions from investors.

[42] I fix total assets at the beginning of the period to prevent the capital ratio to be driven by active balance sheet management. However, here I am interested in the changes in capital over time. Therefore, I only fix total assets at the beginning of the period so that changes in the capital ratio are only driven by mark-to-market activities as well as equity issuance.

2.5 Price Change Dynamics

2.5.1 Investment Behavior and Future Price Changes

In order to test how prices of securities move after various institutions have bought them, I regress the difference of the k period ahead log of the price and the current log of the price, $\Delta Price_{s,t+k}$, on the netbuy variable for each institution type X for security s as follows:

$$\Delta Price_{s,t+k} = \beta_1 Netbuy_{s,t}^{X} + \alpha_t + \epsilon_{s,t+k} \tag{2.9}$$

where

$$\Delta Price_{s,t+k} = Price_{s,t+k} - Price_{s,t} \tag{2.10}$$

and the price is expressed in logs and time fixed effects, α_t, control for market-wide developments. Column (1) of Table 2.9, Table 2.10 and Table 2.11 report results for k=1. The results show that the price of a security increases after banks and investment funds have acquired the security. These results are in line with Adrian et al. (2010a,b, 2011) who show that the investment behavior of banks can predict price changes and can even stimulate the economy. A doubling in the nominal amount held is associated with a 0.12 percent increase in the bond price in the next quarter for banks and 0.2 percent for investment funds.

In contrast to the prices of securities that have been bought by banks and investment funds, the prices of securities that have been bought by insurance companies and pension funds do not increase significantly. Columns (2) and (3) of Table 2.11 show that prices decrease two and three quarters after insurance companies and pension funds have bought them. A doubling in the amount bought by insurance companies and pension funds result on average in 0.2 percent lower bond prices after two and three quarters. However, after ten quarters the results are reversed. For k=10, the prices of bonds have increased after insurance companies and pension funds have bought them and decreased when banks and investment funds have bought them. After twelve quarters bond prices are 1.7 percent higher when insurance companies and pension funds have doubled their position. These findings are consistent with the impression given by Figure 2.4 that the counter-cyclical strategy of insurance companies and pension funds is not profitable at short horizons but outperforms pro-cyclical investment behavior in the medium run.

2.5.2 Momentum and Reversal of Prices

Prior evidence suggests that price changes are positively auto-correlated at short horizons but negatively correlated at longer horizons (Cutler et al., 1990, 1991; Moskowitz et al., 2012).[43] This would support the results of section 5.1 that pro-cyclical investment behavior is profitable at short horizons while counter-cyclical investment behavior pays off at longer horizons. According to Cutler et al. (1990) price changes reflect a fundamental and a transitory component. While the fundamental component follows a random walk, the transitory component follows a first-order autoregressive process that is likely driven by a dominance of noise traders who overreact to fundamental news. In the absence of noise traders, investors are not expected to change their security holdings as a response to price changes (Milgrom and Stokey, 1982). After rejecting this hypothesis in section 3, this section delivers complementary evidence on the possible channel. Positive feedback investing may be rational when the investment horizon is short and one has a strong loss aversion at short horizons. In this case, it may be rational to have a positive demand elasticity to price changes. In contrast, counter-cyclical investors, who have a negative demand elasticity to price changes, may have a low short-term loss aversion but instead aim to maximize their profits at long horizons.

Although the positive auto-correlation at short horizons and the negative auto-correlation at longer horizons has been pointed out by previous papers, I study whether the same pattern also holds in my data. Therefore, I estimate the following specification:

$$\Delta Price_{s,t+k} = \alpha_{t+k} + \beta_1 \Delta Price_{s,t} + \epsilon_{i,t+k} \tag{2.11}$$

Table 2.12 shows that banks and investment funds can indeed avoid short-term losses by acting pro-cyclically, as price changes are positively auto-correlated at short horizons. In contrast, as insurance companies' and pension funds' constraints do not tighten when they suffer losses on their security holdings, this may enable them to step in when bonds are cheap. That this counter-cyclical investment strategy can be profitable when prices revert can be seen in Table 2.12. Given that insurance companies and pension funds act on longer horizons, one would expect them to buy potentially undervalued securities as they have the comparative advantage to wait until the prices revert. I turn to this topic in the next section.

[43]Vayanos and Woolley (2013) propose a model of momentum and reversal.

2.6 Additional Tests

2.6.1 Investment Behavior and Excess Bond Yields

As shown above, banks and investment funds act in a pro-cyclical manner to price changes. This behavior can be profitable in the short run but is less profitable than the investment behavior of insurance companies and pension funds in the medium run. Since banks and investment funds trade on shorter horizons than do insurance companies and pension funds, they might be more averse to liquidity risk. In this section, I define an excess bond yield as the yield spread of a security that cannot be justified by credit risk to test this hypothesis. An increase in the excess bond yield reflects an increase in returns without an increase in credit risk. That the excess bond yield increases might be due to lower liquidity, which may not be part of the fundamental value. Therefore, changes in the excess bond yield could arguably be interpreted as variation of the non-fundamental component of the bond.

My approach is similar to the one of Gilchrist and Zakrajšek (2012). First, I define a risk-free yield for five maturity buckets, i.e. for 1-3 years, 3-5 years, 5-7 years, 10-20 years, above 20 years.[44] I define the risk-free yield as the yield of a German government security in each benchmark. In order to define an excess bond yield, I regress the security-specific yield-to-maturity on the risk-free yield of its maturity bucket, a categorial credit rating variable and a security fixed effect to control for time-invariant security-specific characteristics such as exchange rate risk if the security is denominated in foreign currency. I estimate the following regression:

$$Yield_{s,t} = \beta_1 Yield^{rf}_{m,t} + \gamma' \mathbf{Rating}_{s,t} + \alpha_s + \epsilon_{s,t} \tag{2.12}$$

where **Rating** is a vector of dummies for each rating category. I take the residual of this regression and define:

$$ExcessBondYield = \epsilon_{s,t} \tag{2.13}$$

Yields may be higher for bonds that are more difficult to sell, especially in times of market turmoil. Illiquidity is only a risk for short-term investors that need to sell securities at short horizons. Investors that hold securities until maturity should not be reluctant to hold these securities. In contrast, these investors should even

[44] I follow Ellul et al. (2011) for the choice of the maturity groups.

buy these securities when the liquidity premium goes up when these also yield higher expected future returns.

Therefore, I investigate which investors are buying and selling bonds whose excess bond yields rise as follows:

$$Netbuy_{s,t}^{X} = \beta_1 \Delta ExcessBondYield + \alpha_s + \alpha_t + \epsilon_{s,t} \tag{2.14}$$

Table 2.13 shows the results of a regression of the netbuy variable on the excess bond yield.[45] Insurance companies and pension funds buy securities whose excess bond yields increase and sell them when the excess bond yield decreases. In particular, column (3) shows that a one percentage point increase in the excess bond yield is associated with a 2.3 percent increase in the nominal amount held. This might be the case because insurance companies and pension funds often hold bonds until maturity and do not have to sell at short notice. In contrast, banks and investment funds buy when the excess bond yield falls and sell when the excess bond yield increases.

If changes in the excess bond yield are interpreted as changes away from their fundamental value, these results suggest that banks and investment funds are pushing away prices from fundamentals and insurance companies and pension funds stabilize prices and push them towards fundamentals. Since banks and investment funds trade more frequently than do insurance companies and pension funds, it may be rational for them to consciously buy securities that are overvalued. Speculating on further price rises indicates that investors attempt to ride the bubble and time the market by selling the security when the price is at the inflection point (Brunnermeier and Nagel, 2004). The behavior of banks to buy securities whose excess bond yield falls is consistent with the model of Shleifer and Vishny (2010) who show that if banks believe that security prices will increase further, they lever up and buy securities.[46] However, once prices start to fall, banks cannot roll over funding and may have to sell securities in order to de-lever again. Alternatively, banks and investment funds may sell securities that trade below their fundamental value if they expect the downward trend to continue further at short horizons, as shown in Table 2.12.

In contrast, return-oriented investors who have a long-term investment horizon

[45]Since the variable Excess Bond Yield is estimated, I bootstrap the standard errors.

[46]This behavior is also consistent with models that predict myopic behavior due to short-term incentives (Stein, 1989).

and potentially hold securities until maturity may be buying up troubled assets when they believe the security is undervalued in order to benefit from future price increases (Hanson and Stein, 2015). In line with the typical behavior of return-oriented investors, insurance companies and pension funds, who may be more risk tolerant due to their long-term liabilities, buy assets whose excess bond yield has risen.This behavior can act as a stabilizing force in bad times and prevent prices from falling by as much as they would otherwise. Selling securities whose excess bond yields are falling and whose prices are potentially rising above their fundamental value on the other side can also prevent bubbles from growing. These types of investors have received rather less attention but are certainly important actors who can prevent the buildup of systemic risk that could materialize in a crisis (Brunnermeier and Sannikov, 2014).

2.6.2 Cyclical Investment Behavior and Risk

2.6.2.1 Credit Risk

While in the previous section I have used the credit rating in order to construct an excess bond yield, I have neither used the credit rating unconditionally in order to test whether the rating of the bond affects their investment behavior, nor have I investigated whether the cyclical investment behavior is different across rating categories. In order to do so, I first construct a dummy that equals one if the security is rated investment grade and zero otherwise. I interact the dummy, *IG*, with the price change. A positive coefficient shows that institutions act relatively more pro-cyclically with respect to investment grade bonds. Table 2.14 shows that the counter-cyclical investment behavior of insurance companies and pension funds is more pronounced for non-investment grade bonds. It also shows that the results are robust along two additional dimensions. First, the price change coefficient is still highly significant even after controlling for the rating category. This allows me to rule out the possibility that price changes due to rating category changes are driving the results, see e.g. Ellul et al. (2011, 2015) and Merrill et al. (2012). Second, cyclical investment bevavior is robust across rating types. For instance, while for insurance companies and pension funds the cyclical investment behavior is different in magnitude for investment grade bonds and non-investment grade bonds, insurance companies and pension funds act counter-cyclically both with respect to investment grade bonds and non-investment grade bonds. On the other side, banks and investment funds act pro-cyclically for both types of categories.

2.6.2.2 Foreign Exchange Rate Risk

Table 2.15 looks at whether the cyclical investment behavior is different for bonds that are denominated in foreign currency. I define a dummy that is equal to one if the bond is denominated in foreign currency and zero otherwise. I interact the dummy FC with the price change coefficient. A positive coefficient indicates that institutions act relatively more pro-cyclically with respect to foreign currency bonds. Table 2.15 shows that the results hold for both domestic currency and foreign currency bonds. The results are, if anything, stronger for foreign currency bonds. This finding underlines the results by Cerutti et al. (2015). They find that emerging markets that rely on investment funds and banks as their main creditors, exhibit relatively higher volatility of their capital inflows. They argue that it is important for emerging markets to monitor their investor base. My results support their hypothesis and do not only apply to cross-border inflows into emerging market countries, but also more generally to both domestic and foreign investors as well as corporates and governments.[47]

2.6.2.3 Market Risk

While the above measures focus on credit and foreign exchange rate risk, I have thus far neglected the interaction between market risk and the price change. To address this, I define a β_{dax} in relation to the German stockmarket index by estimating the following specification for each security s:

$$\Delta Price_t = \alpha + \beta_{dax} \Delta Dax_t + \epsilon_t \tag{2.15}$$

where Dax is the log of the German stockmarket index. Then, I obtain the beta coefficient for each security, β_{dax}, which reflects the relation of the price change with the stockmarket. A positive and large β_{dax} indicates high systematic risk with respect to the stockmarket. A coefficient of one reflects that the price of the security moves in tandem with the stockmarket, on average. An investor whose benchmark portfolio is on average highly correlated with the German stockmarket can buy securities with a low or even negative β_{dax} in order to hedge exposure to the stockmarket. Table 2.16 shows whether the cyclical investment behavior of the various institutions differs depending on the beta of the security in question. For this, I interact the β_{dax} with the price change of the security. A positive coefficient

[47] Table 2.18 shows the results for German and foreign bonds.

on the interaction term shows that institutions act relatively more pro-cyclically or less counter-cyclically with respect to bonds that reflect a higher systematic risk with respect to the stockmarket. Column (4) shows that insurance companies and pension funds act relatively more counter-cyclically with respect to bonds that have a larger beta. In contrast, banks act relatively more pro-cyclically with respect to these bonds.[48]

Table 2.20 shows the same analysis but instead of using the price change of the security and the percentage increase in the stockmarket index. I use the security-specific yield and the risk-free yield (rf) to define β_{rf}.[49] Securities that have a large β_{rf} move in tandem with the risk-free securities and can be considered less risky. Table 2.20 shows that the beta with respect to the risk-free yield does not seem to be important in determining the cyclical investment behavior.[50]

One other dimension of risk is the volatility of the bond. I define the volatility of the bond as its sample standard deviation and interact it with the price change. A positive coefficient shows that institutions act relatively more pro-cyclically with respect to more volatile bonds. Table 2.22 shows that banks seem to act relatively more pro-cyclically with respect to less volatile bonds.

In order to investigate further whether the cyclical investment behavior changes over the financial cycle, I look at times of a high VIX in the next step. When market liquidity is low, pro-cyclical investment behavior can lead to strong market distortions and investors may be forced to sell at fire-sale prices because they have to meet margin calls or they cannot roll over their liabilities. If prices fall and investors act pro-cyclically during volatile times, their redemption can trigger a spiral of market and funding liquidity (Brunnermeier and Pedersen, 2009). Amihud et al. (2006) and Amihud and Mendelson (1986), show that short-term investors avoid illiquid securities in times of high expected volatility. The probability that illiquid assets will have to be sold at fire-sale prices increases when volatility increases. Hence, funds with daily reception notice should not hold illiquid assets in volatile times if they want to avoid selling off assets at fire-sale prices. In contrast, long-term investors can benefit from a liquidity premium as short-term investors avoid illiquid securities in times of high expected volatility.

[48]Table 2.19 show the results when the covariance instead of the β_{dax} is used.

[49]I again use the German government bond in the respective maturity bucket as the risk-free yield.

[50]Table 2.21 shows the results for the covariance instead of the beta.

In order to test whether the cyclical behavior of financial institutions intensifies in volatile times, I interact the VIX with the change in the price. Column (1) of Table 2.23 shows that as soon as the VIX increases, investment funds exacerbate the pro-cyclicality, which is in favor of the hypothesis that investment funds act relatively more pro-cyclically in times when asset prices are down. However, once time fixed effects are included, the result diminishes. When the market in general is more volatile, measured by a high VIX, investment funds and insurance companies and pension funds act relatively less counter-cyclically (Table 2.23). However, even large movements in the VIX, e.g. a 100 percent increase in the VIX, does not make insurance companies and pension funds act pro-cyclically. In addition, the result also diminishes when time fixed effects are included.

This suggests that the results are not driven by specific time periods, which I test more formally in the next section.

2.6.3 Crisis Split

In Table 2.24, Table 2.25 and Table 2.26 I divide the sample into three subsamples: pre-crisis (2006 Q1:2008 Q1), crisis (2008 Q2:2012 Q3), and post-crisis (2012 Q4:2014 Q4).[51] Even in this very conservative specification with period-specific security fixed effects, the results are remarkably stable. Table 2.24 show the results for investment funds. In the pre-crisis period, a 10 percent increase in the price is associated with a 1.3 percent increase in the nominal holdings of the security when security fixed effects are included and an increase of 0.5 percent when both security and time fixed effects are included. In the crisis they increase the nominal amount both with and without time fixed effects by 1.1 percent. In the post-crisis period the response changes to 0.9 percent and 1.7 percent, respectively.

Table 2.25 shows that insurance companies and pension funds acted relatively more counter-cyclically before the crisis. However, the counter-cyclical investment behavior is still strong in the crisis and post-crisis period with elasticities between 0.16 and 0.53 depending on the specification.

For banks, the pro-cyclical investment behavior has been more pronounced before and after the crisis with magnitudes of 0.5 to 0.8. During the crisis, the response was lower in magnitude but still highly significant at the 1 percent

[51] 2008 Q2 is the first quarter in which Germany’s seasonally adjusted quarterly GDP dropped the first time in my sample. The end of the crisis period is defined as the quarter after Mario Draghi’s announcement to do “whatever it takes to preserve the Euro", which happened in 2012 Q3.

significance level (Table 2.26). Banks reduced their holdings by 2.5 percent and 3 percent as a response to a 10 percent price decrease, depending on the specification.

2.6.4 Further Robustness

Additionally, I test whether the response is robust for both buying and selling behavior. This can be confirmed in Table 2.27. Investment funds and banks buy when price rise and sell when they fall. In contrast, insurance companies and pension funds buy when prices fall and sell when prices rise.

Until now I have assumed that the coefficient is the same for corporate and government bonds. In Table 2.28, I relax this assumption and allow the coefficient to vary by issuing sector. In particular, I define a dummy for each of the three issuing sectors: government, banks and other-financial corporates (ofc). I interact the price change with the respective dummies. A positive coefficient can be interpreted as evidence for relatively more pro-cyclical investment behavior compared to the benchmark of non-financial corporate bonds (nfc). In general, I confirm my previous findings. In most cases, the highest quantitative responses to price changes are with respect to non-financial corporate bonds. A 10 percent increase in the price is associated with a 1.2 percent and 8.6 percent increase in the amount held for investment funds and banks, respectively, but a 31 percent decrease by insurance companies and pension funds. While the sign of the coefficients is still in line with the benchmark model, the magnitude of the cyclical investment behavior varies depending on the issuer type. Insurance companies and pension funds act relatively less counter-cyclically with respect to bank, other-financial corporate and government bonds. Banks and investment funds act relatively less pro-cyclically with respect to government bonds but not significantly different with respect to other-financial corporate and bank bonds.

To test the sensitivity of the price change coefficient to the inclusion of further controls, Table 2.29 shows a summary of the lagged price change coefficients for various specifications. Controlling for more unobserved and observed characteristics also indicates whether the sectors respond to relative price changes of the debt securities or whether the investment decision is driven by broad market valuations. Creating a more coherent sample across the sectors sheds light on the question of whether the coefficients are driven by a sample selection bias. The coefficient is consistently positive for investment funds and banks and negative for insurance companies and pension funds. Row (1) is the result of a simple regression of the netbuy variable on the lagged price change excluding any controls. While the inclusion of security fixed effects allows to make judgement about the investment behavior in a specific security over time, excluding security fixed effects does not only capture the time-series variation but also the cross-sectional variation. Including security fixed effects controls for all time-invariant security-specific characteristics, such as the coupon or the maturity date, but of course also for the issuing country of the security. The approach using security fixed effects focuses on one specific security and attempts to explain the buying and selling behavior over time.[52] Both regressions show that, unconditional and conditional on time-invariant security characteristics, banks and investment funds respond pro-cyclically to price changes, while insurance companies and pension funds act counter-cyclically.

Row (3) includes macro controls for Germany, i.e. German GDP growth, inflation, the 10-year government bond yield, the EONIA and the VIX. Row (4) assigns country-specific controls to the country of issue. Row (5) absorbs observed and unobserved country-specific time-varying characteristics. In order to examine how financial institutions invest in specific securities, compared to other securities that were issued in the same sector of the same country, the specification is also saturated with sector$*$country$*$time fixed effects. This controls for unobserved and observed time-varying heterogeneity, such as the time-varying common component of a specific asset class. In particular, it adds the issuing sector dimension for banks, other-financial corporations, non-financial corporations, and governments in their capacity as issuing sectors. Hence, for each issuing sector of a given country I control for the average amount bought or sold at a given point in time, which controls for broad market valuations of this index. Even within this benchmark, banks and investment funds buy securities that have increased in value. However, while for investment funds and banks the coefficients are even higher than in specification (5), the coefficient for insurance companies and pension funds is relatively lower. This indicates that insurance companies and pension funds tend to buy securities that are included in a falling index. In contrast, banks' and investment funds' pro-cyclical investment behavior is also driven by idiosyncratic movements of the security compared to its benchmark.[53] To make the sample of securities held

[52]The coefficients vary slightly from Table 2.3 as the sample is harmonized in Table 2.29 to make coefficients better comparable.

[53]In Table 2.30, I decompose the price change is into a broad market valuation of the issuing sector-country index and an idiosyncratic part. For insurance companies and pension funds and banks the broad price change movement is more important than the relative one. In contrast, for

more comparable, row (7) restricts the security sample to all securities that have been held by insurance companies and pension funds, investment funds and banks at least once throughout the sample.

investment funds the relative price change is more important than the broad index.

2.7 Conclusion

This paper analyzes the cyclical investment behavior of investment funds, banks and insurance companies and pension funds. I show that banks and investment funds are pro-cyclical investors with respect to price changes. In contrast, insurance companies and pension funds respond counter-cyclically to price changes: they buy when prices have fallen and sell when prices have gone up.

One channel that could generate the heterogeneity in the cyclical investment behavior is based on the investors' balance sheet dynamics. I provide evidence that is consistent with this channel by exploiting cross-sectional heterogeneity between institutions for banks and investment funds. The pro-cyclical investment behavior is stronger for banks that are relatively weaker capitalized and investment funds that face relatively more outflows. Although investment funds use almost no leverage, both investment funds and banks are sensitive to short-term losses on their security holdings. In order to avoid these losses, they act pro-cyclically as prices exhibit a short-term momentum factor. Since insurance companies' and pension funds' balance sheets are more resilient to short-term losses, they can act in a counter-cyclical manner.

The pro-cyclical investment behavior of investment funds and banks resulted in relatively mild losses during the European sovereign debt crisis. Although insurance companies and pension funds suffered severe losses during the crisis, they outperformed banks and investment funds in the medium run.

The results suggest that the investment behavior of insurance companies and pension funds can be a stabilizing force on capital markets. In contrast, the investment behavior of banks and investment funds can exacerbate price dynamics and lead to excessive volatility in capital markets. These results underline the findings of Cerutti et al. (2015) who argue that it can be hazardous for countries to rely on investment funds and banks as their main investors.

Panel A: Insurance Companies and Pension Funds

	Holdings	Buy	Sell	Netbuy	Buy %	Sell %	ΔPrice
Mean	22.634	11.021	9.768	-0.003	0.311	-0.305	0.001
Std.	78.122	35.295	33.349	0.670	0.577	0.612	0.037
Obs.	136954	14665	15183	29848	14665	15183	734517

Panel B: Investment Funds

	Holdings	Buy	Sell	Netbuy	Buy %	Sell %	ΔPrice
Mean	31.842	5.887	6.192	-0.012	0.218	-0.212	0.001
Std.	115.805	26.240	24.487	0.438	0.389	0.377	0.037
Obs.	383521	107737	124584	232321	107737	124584	734517

Panel C: Banks

	Holdings	Buy	Sell	Netbuy	Buy %	Sell %	ΔPrice
Mean	57.641	12.749	15.800	-0.002	0.372	-0.407	0.001
Std.	167.278	47.811	58.529	0.812	0.669	0.758	0.037
Obs.	475782	62553	57783	120336	62553	57783	734517

Holdings is the nominal value held if a security is held (in million Euros). Buy and sell refers to the amount bought and sold in million Euros. Netbuy is the change in the log of the nominal amount held. Buy % (Sell %) is the change in the log of the nominal amount held if positive (negative). ΔPrice is the change in the log of the price. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2004 Q4 - 2014 Q4; author's calculations.

Table 2.1: *Summary Statistics*

	Dependent variable: Netbuy					
	(1)	(2)	(3)	(4)	(5)	(6)
ΔPrice	-0.576***	-0.850***	-0.429***			
	(0.115)	(0.116)	(0.132)			
ΔPrice $*$ Funds	0.718***	0.955***	0.565***	0.647***	0.861***	0.428**
	(0.117)	(0.118)	(0.134)	(0.145)	(0.159)	(0.186)
ΔPrice $*$ Banks	0.912***	1.191***	0.789***	0.993***	1.359***	0.855***
	(0.140)	(0.143)	(0.158)	(0.176)	(0.186)	(0.217)
R-squared	0.0834	0.119	0.123	0.453	0.529	0.532
Observations	386618	382505	382505	147449	147449	147449
Security FE	Yes	-	-	-	-	-
Time FE	Yes	No	-	-	-	-
Security$*$Time FE	No	No	No	Yes	Yes	Yes
Sector$*$Time FE	No	No	Yes	No	No	Yes
Security$*$Sector FE	No	Yes	Yes	No	Yes	Yes

The dependent variable is the change in the log of the nominal amount held. Δ*Price* is the change in the log of the price and is lagged by one quarter. *Banks* is a dummy that equals one for banks and zero otherwise. *Funds* is a dummy that equals one for investment funds and zero otherwise. The benchmark is insurance companies and pension funds. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table 2.2: *Heterogeneity in Cyclical Investment Behavior — Interactions*

	Dependent variable: Netbuy					
	Funds		ICPF		Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔPrice	0.105***	0.136***	-0.850***	-0.429***	0.341***	0.361***
	(0.024)	(0.026)	(0.116)	(0.132)	(0.084)	(0.088)
R-squared	0.120	0.126	0.161	0.173	0.112	0.114
Observations	232321	232321	29848	29848	120336	120336
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes

The dependent variable is the change in the log of the nominal amount held. $\Delta Price$ is the change in the log of the price and is lagged by one quarter. Column (1)-(2) estimate the specification for the investment fund sector. Column (3)-(4) estimate the specification for the insurance companies and pension fund sector. Column (5)-(6) estimate the specification for the banking sector. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table 2.3: *Heterogeneity in Cyclical Investment Behavior — Sample Split*

	Dependent variable: Netbuy			
	(1)	(2)	(3)	(4)
ΔPrice	0.584**	0.647**		
	(0.232)	(0.271)		
ΔPrice ∗ Capital	-10.44**	-24.52*	-18.67***	-31.49**
	(4.300)	(12.952)	(6.833)	(14.146)
R-squared	0.116	0.126	0.236	0.247
Observations	1643361	1643361	1643361	1643361
Security FE	Yes	Yes	-	-
Institution FE	Yes	-	Yes	-
Time FE	Yes	-	-	-
Institution∗Time FE	No	Yes	No	Yes
Security∗Time FE	No	No	Yes	Yes

The dependent variable is the change in the log of the nominal amount held for banks on the institution-level. Δ*Price* is the change in the log of the price and is lagged by one quarter. *Capital* is equity as a ratio of its total assets at the beginning of the period. *Capital* is demeaned by the average across banks. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Standard errors are double clustered at the security and institution-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, monthly bank balance sheet statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table 2.4: *Bank Heterogeneity*

	Dependent variable: Netbuy			
	(1)	(2)	(3)	(4)
ΔPrice $*$ Capital	-4.021	-52.06***	-7.049	2.197
	(34.382)	(18.561)	(36.442)	(39.385)
R-squared	0.218	0.258	0.289	0.286
Observations	440880	692433	198374	311674
Institution$*$Time FE	Yes	Yes	Yes	Yes
Security$*$Time FE	Yes	Yes	Yes	Yes
Sample	Pre-Crisis	Crisis	Post-Crisis	Post-Reg. Reform

The dependent variable is the change in the log of the nominal amount held for banks on the institution-level. Δ*Price* is the change in the log of the price and is lagged by one quarter. *Capital* is equity as a ratio of its total assets at the beginning of the period. *Capital* is demeaned by the average across banks. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). *Pre-Crisis* refers to the period 2006 Q1:2008 Q1, *Crisis* refers to 2008 Q2:2012 Q3, *Post-crisis* refers to 2012 Q4:2013 Q4 and *Post-Reg. Reform* refers to 2014 Q1:2014 Q4. Standard errors are in parentheses. Standard errors are double clustered at the security and institution-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, monthly bank balance sheet statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table 2.5: *Bank Heterogeneity across Time*

	Dependent variable: Netbuy			
	(1)	(2)	(3)	(4)
ΔPrice	0.0885	0.177		
	(0.302)	(0.277)		
ΔPrice ∗ Net Outflow	1.486**	1.259**	1.920***	1.789***
	(0.722)	(0.572)	(0.608)	(0.584)
R-squared	0.340	0.435	0.422	0.507
Observations	2554558	2554558	2554558	2554558
Security FE	Yes	Yes	-	-
Time FE	Yes	-	Yes	-
Institution FE	Yes	-	-	-
Institution∗Time FE	No	Yes	No	Yes
Security∗Time FE	No	No	Yes	Yes

The dependent variable is the change in the log of the nominal amount held for investment funds on the institution-level. *ΔPrice* is the change in the log of the price. *Net Outflow* is the negative of the change in the face value of shares outstanding as a ratio of the lagged Net Asset Value. The level of *Net Outflow* is included in the specification whenever not collinear with the fixed effects. All independent variables are lagged by one quarter. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Standard errors are double clustered at the security and institution-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, investment fund statistics, 2009 Q4 - 2014 Q4; author's calculations.

Table 2.6: *Investment Fund Heterogeneity*

	Dependent variable: Netbuy				
	(1)	(2)	(3)	(4)	(5)
ΔPrice	-0.831***	-0.416***	-0.926***	-0.926***	-0.602***
	(0.115)	(0.132)	(0.136)	(0.136)	(0.159)
ΔPrice $*$ ΔMismatch	32.26***	34.77***	40.56***	40.56***	37.98***
	(6.822)	(8.447)	(9.022)	(9.022)	(10.102)
R-squared	0.162	0.174	0.168	0.168	0.174
Observations	29848	29848	29848	29848	29848
Security FE	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	No	Yes
Macro Controls	No	-	Yes	Yes	-
Macro Interactions	No	No	No	Yes	Yes

The dependent variable is the change in the log of the nominal amount held for insurance companies and pension funds. Δ*Price* is the change in the log of the price. Δ*Mismatch* is the change in the ratio of long-term liabilities to long-term assets of insurance companies and pension funds. The level of Δ*Mismatch* is included in the specification whenever not collinear with the fixed effects. Macro controls include the German GDP growth, inflation, the 10-year government bond yield, the EONIA and the VIX. Macro interaction are the respective interaction of the macro controls with the price change. All independent variables are lagged by one quarter. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, Deutsche Bundesbank, time series database, banks and other financial institutions, insurance corporations and pension funds, 2005 Q4 - 2014 Q4; author's calculations.

Table 2.7: *ICPF Heterogeneity*

	Δ Mismatch	Capital		Net Outflows	
	(1)	(2)	(3)	(4)	(5)
Net Capital Gains	0.0542	0.0937***	0.257***	-0.217***	-0.0822***
	(0.054)	(0.034)	(0.008)	(0.072)	(0.007)
R-squared	0.0292	0.186	0.807	0.303	0.335
Observations	36	36	59563	36	92870
Time FE	-	-	Yes	-	Yes
Institution FE	-	-	Yes	-	Yes

The dependent variable Δ*Mismatch* is the change in the ratio of long-term liabilities to long-term assets of insurance companies and pension funds; *Capital* is equity as a ratio of its total assets with assets being fixed at the beginning of the period; *Net Outflow* is the negative of the change in the face value of shares outstanding as a ratio of the lagged Net Asset Value. *Net Capital Gains* are sector or institution specific net capital gains on security holdings and lagged by one quarter. Columns (1), (2) & (4) are on the sector sector-level. Columns (3) & (5) are on the institution-level. Fixed effects are either included (Yes), not included (No) or cannot be included (-). Robust standard errors are in parentheses. Standard errors are clustered at the institution-level and robust to heteroskedasticity and autocorrelation in column (3) and (5). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, Deutsche Bundesbank, time series database, banks and other financial institutions, investment fund statistics, monthly balance sheet statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table 2.8: *Capital Gains and Balance Sheet Constraints*

	Dependent variable: $Price_{t+k} - Price_t$							
	k=1	k=2	k=3	k=4	k=6	k=8	k=10	k=12
$Netbuy_{Funds}$	0.201***	0.209	-0.0514	-0.0321	-0.893***	-1.363***	-1.570***	-0.392
	(0.067)	(0.132)	(0.163)	(0.216)	(0.307)	(0.363)	(0.425)	(0.408)
R-squared	0.0253	0.0265	0.0267	0.0314	0.0356	0.0389	0.0471	0.0534
Observations	508645	458306	413195	371909	303699	243732	195595	154294
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable is the change in the log of the price between quarter t+k and t. $Netbuy_{Funds}$ is the change in the log of the nominal amount held of investment funds. Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table 2.9: *Future Price Changes — Investment Funds*

	Dependent variable: $Price_{t+k}$-$Price_t$							
	k=1	k=2	k=3	k=4	k=6	k=8	k=10	k=12
$Netbuy_{Banks}$	0.123***	-0.0182	-0.319***	-0.353***	-0.257**	-0.251*	-0.227	-0.736***
	(0.036)	(0.053)	(0.082)	(0.090)	(0.106)	(0.130)	(0.167)	(0.175)
R-squared	0.0253	0.0265	0.0268	0.0315	0.0355	0.0388	0.0469	0.0536
Observations	508645	458306	413195	371909	303699	243732	195595	154294
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable is the change in the log of the price between quarter t+k and t. $Netbuy_{Banks}$ is the change in the log of the nominal amount held of banks. Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table 2.10: *Future Price Changes — Banks*

	Dependent variable: $Price_{t+k}$-$Price_t$							
	k=1	k=2	k=3	k=4	k=6	k=8	k=10	k=12
$Netbuy_{ICPF}$	0.0714	-0.213**	-0.233*	-0.188	-0.497**	-0.277	0.761***	1.753***
	(0.056)	(0.097)	(0.126)	(0.169)	(0.243)	(0.255)	(0.260)	(0.268)
R-squared	0.0253	0.0265	0.0267	0.0314	0.0355	0.0387	0.0470	0.0536
Observations	508645	458306	413195	371909	303699	243732	195595	154294
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable is the change in the log of the price between quarter t+k and t. $Netbuy_{ICPF}$ is the change in the log of the nominal amount held of insurance companies and pension funds. Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table 2.11: *Future Price Changes — ICPF*

	Dependent variable: $\text{Price}_{t+k} - \text{Price}_t$							
	k=1	k=2	k=3	k=4	k=6	k=8	k=10	k=12
ΔPrice	0.0460***	0.0358***	-0.0173***	0.00378	0.00332	-0.0162	-0.122***	-0.0741***
	(0.003)	(0.004)	(0.005)	(0.006)	(0.008)	(0.011)	(0.014)	(0.018)
R-squared	0.191	0.193	0.182	0.177	0.158	0.115	0.0479	0.0420
Observations	445056	394264	352757	314980	247176	193422	147924	113408
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable is the change in the log of the price between quarter t+k and t. $\Delta Price$ is the change in the log of the price between quarter t and t-1. Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table 2.12: *Momentum and Reversal in Prices*

	Dependent variable: Netbuy					
	Funds		ICPF		Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔExcess Yield	-0.00225*	-0.00259*	0.0225***	0.0110*	-0.0222***	-0.0205***
	(0.001)	(0.001)	(0.005)	(0.007)	(0.004)	(0.003)
R-squared	0.160	0.165	0.336	0.346	0.201	0.203
Observations	190824	190824	24882	24882	90967	90967
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes

The dependent variable is the change in the log of the nominal amount held. Δ *Excess Yield* is the lagged change in the residual of a regression of the yield-to-maturity on the risk-free yield within its maturity bucket, an indicator variable for the credit rating and a security fixed effect. Column (1)-(2) estimate the specification for the investment fund sector. Column (3)-(4) estimate the specification for the insurance companies and pension fund sector. Column (5)-(6) estimate the specification for the banking sector. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Bootstrapped standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, Bloomberg, Datastream, 2005 Q4 - 2014 Q4; author's calculations.

Table 2.13: *Excess Bond Yield*

	Dependent variable: Netbuy					
	Funds		ICPF		Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔPrice	0.0800***	0.0989***	-1.253***	-0.921***	0.262**	0.271**
	(0.028)	(0.030)	(0.198)	(0.196)	(0.120)	(0.120)
IG	0.000435	-0.0164	0.137**	0.0400	0.0398	0.0121
	(0.019)	(0.019)	(0.061)	(0.066)	(0.035)	(0.035)
ΔPrice ∗ IG	0.0988*	0.149***	0.683***	0.859***	0.184	0.212
	(0.051)	(0.052)	(0.247)	(0.248)	(0.167)	(0.169)
R-squared	0.120	0.126	0.161	0.174	0.112	0.114
Observations	232321	232321	29848	29848	120336	120336
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes

The dependent variable is the change in the log of the nominal amount held. Δ*Price* is the change in the log of the price and is lagged by one quarter. *IG* is a dummy that equals one if the security is rated investment grade and zero otherwise and is lagged by one quarter. Column (1)-(2) estimate the specification for the investment fund sector. Column (3)-(4) estimate the specification for the insurance companies and pension fund sector. Column (5)-(6) estimate the specification for the banking sector. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, Bloomberg, Datastream, 2005 Q4 - 2014 Q4; author's calculations.

Table 2.14: *Credit Rating*

	Dependent variable: Netbuy					
	Funds		ICPF		Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔPrice	0.101**	0.212***	-0.709***	-0.243	0.165*	0.198*
	(0.050)	(0.053)	(0.131)	(0.151)	(0.099)	(0.105)
ΔPrice ∗ FC	0.00445	-0.0921	-0.588**	-0.763***	0.509***	0.452**
	(0.057)	(0.059)	(0.284)	(0.281)	(0.184)	(0.185)
R-squared	0.120	0.126	0.161	0.173	0.112	0.114
Observations	232314	232314	29848	29848	120336	120336
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes

The dependent variable is the change in the log of the nominal amount held. Δ*Price* is the change in the log of the price and is lagged by one quarter. *FC* is a dummy that equals one if the security is denominated in foreign currency and zero otherwise. Column (1)-(2) estimate the specification for the investment fund sector. Column (3)-(4) estimate the specification for the insurance companies and pension fund sector. Column (5)-(6) estimate the specification for the banking sector. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table 2.15: *Foreign Currency Bonds*

	Dependent variable: Netbuy					
	Funds		ICPF		Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔPrice	0.122***	0.162***	-0.841***	-0.342**	0.275***	0.300***
	(0.032)	(0.036)	(0.144)	(0.147)	(0.099)	(0.095)
ΔPrice $*\ \beta_{Dax}$	-0.135	-0.210	-0.651	-1.551**	0.841**	0.670**
	(0.141)	(0.188)	(0.509)	(0.725)	(0.353)	(0.326)
R-squared	0.116	0.122	0.160	0.172	0.109	0.110
Observations	230374	230374	29609	29609	117616	117616
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes

The dependent variable is the change in the log of the nominal amount held. Δ*Price* is the change in the log of the price and is lagged by one quarter. β_{Dax} is the coefficient obtained from a regression of the price change of the security on the percentage change of the German stockmarket index (Dax). β_{Dax} is demeaned and standardized by the sample standard deviation. Column (1)-(2) estimate the specification for the investment fund sector. Column (3)-(4) estimate the specification for the insurance companies and pension fund sector. Column (5)-(6) estimate the specification for the banking sector. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Bootstrapped standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, Bloomberg, Datastream, 2005 Q4 - 2014 Q4; author's calculations.

Table 2.16: *β Stockmarket*

Variable	Funds	ICPF	Banks
Government	54.9	53.2	33.1
OFC	7.5	7.3	9.8
NFC	8.3	3.9	1.5
Banks	29.3	35.5	55.5
Euro	84.2	92.2	95.1
USD	11.8	2.4	3.4
Other Currency	4.2	5.6	1.8
Domestic	39.6	39.5	73.6
Foreign	60.7	60.7	26.7

Percentage debt securities holdings of investment funds (*Funds*), insurance companies and pension funds (*ICPF*) and *Banks* issued by the Government, Other-Financial Corporations (OFC), Non-Financial Corporations (NFC), Banks, in Euros, US Dollars (USD), other currency and by domestic or foreign residents. Values are averages over the sample period. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2004 Q4 - 2014 Q4; author's calculations.

Table 2.17: *Bond Holdings of German Investors (in %)*

	Dependent variable: Netbuy					
	Funds		ICPF		Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔPrice	0.114***	0.142***	-0.941***	-0.509***	0.383***	0.406***
	(0.025)	(0.027)	(0.149)	(0.157)	(0.103)	(0.104)
ΔPrice ∗ German	-0.161*	-0.107	0.293	0.279	-0.129	-0.142
	(0.088)	(0.089)	(0.229)	(0.239)	(0.179)	(0.182)
R-squared	0.120	0.126	0.161	0.173	0.112	0.114
Observations	232321	232321	29848	29848	120336	120336
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes

The dependent variable is the change in the log of the nominal amount held. *ΔPrice* is the change in the log of the price and is lagged by one quarter. *German* is a dummy that equals one if the country of issue is Germany and zero otherwise. Column (1)-(2) estimate the specification for the investment fund sector. Column (3)-(4) estimate the specification for the insurance companies and pension fund sector. Column (5)-(6) estimate the specification for the banking sector. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table 2.18: *German vs. Foreign Bonds*

	Dependent variable: Netbuy					
	Funds		ICPF		Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔPrice	0.0850***	0.119***	-0.934***	-0.519***	0.255***	0.269**
	(0.033)	(0.039)	(0.154)	(0.160)	(0.096)	(0.110)
ΔPrice$*cov_{\Delta Price,Dax}$	0.0104	0.00887	0.0793	0.0536	0.106*	0.0979*
	(0.015)	(0.017)	(0.087)	(0.082)	(0.056)	(0.056)
R-squared	0.120	0.126	0.159	0.171	0.111	0.113
Observations	226614	226614	29432	29432	119032	119032
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes

The dependent variable is the change in the log of the nominal amount held. $\Delta Price$ is the change in the log of the price and is lagged by one quarter. $cov_{\Delta Price,Dax}$ is the covariance of the price change of the security and the percentage change of the German stockmarket index (Dax). $cov_{\Delta Price,Dax}$ is demeaned and standardized by the sample standard deviation. Column (1)-(2) estimate the specification for the investment fund sector. Column (3)-(4) estimate the specification for the insurance companies and pension fund sector. Column (5)-(6) estimate the specification for the banking sector. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Bootstrapped standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, Bloomberg, Datastream, 2005 Q4 - 2014 Q4; author's calculations.

Table 2.19: *Covariance Stockmarket*

	Dependent variable: Netbuy					
	Funds		ICPF		Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔPrice	0.0964***	0.131***	-0.859***	-0.442***	0.349***	0.364***
	(0.027)	(0.036)	(0.143)	(0.152)	(0.091)	(0.111)
ΔPrice $* \beta_{rf}$	0.00803	0.00553	0.162	0.118	-0.0136	-0.00962
	(0.020)	(0.016)	(0.128)	(0.107)	(0.049)	(0.066)
R-squared	0.111	0.117	0.158	0.170	0.106	0.108
Observations	221671	221671	28844	28844	112615	112615
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes

The dependent variable is the change in the log of the nominal amount held. Δ*Price* is the change in the log of the price and is lagged by one quarter. β_{rf} is the coefficient obtained from a regression of the yield of the security on on the risk-free yield within its maturity bucket. β_{rf} is demeaned and standardized by the sample standard deviation. Column (1)-(2) estimate the specification for the investment fund sector. Column (3)-(4) estimate the specification for the insurance companies and pension fund sector. Column (5)-(6) estimate the specification for the banking sector. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Bootstrapped standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, Bloomberg, Datastream, 2005 Q4 - 2014 Q4; author's calculations.

Table 2.20: *β Risk-free Yield*

	Dependent variable: Netbuy					
	Funds		ICPF		Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔPrice	0.0991***	0.133***	-0.894***	-0.488***	0.346***	0.364***
	(0.025)	(0.034)	(0.165)	(0.138)	(0.122)	(0.101)
ΔPrice*$cov_{yield,rf}$	-0.0263	-0.0396**	0.0643	0.0723	0.00779	0.0168
	(0.024)	(0.018)	(0.106)	(0.125)	(0.057)	(0.054)
R-squared	0.113	0.119	0.159	0.171	0.106	0.108
Observations	217641	217641	28829	28829	112092	112092
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes

The dependent variable is the change in the log of the nominal amount held. $\Delta Price$ is the change in the log of the price and is lagged by one quarter. $cov_{yield,rf}$ is the covariance of the yield of the security and the risk-free yield within its maturity bucket. $cov_{yield,rf}$ is demeaned and standardized by the sample standard deviation. Column (1)-(2) estimate the specification for the investment fund sector. Column (3)-(4) estimate the specification for the insurance companies and pension fund sector. Column (5)-(6) estimate the specification for the banking sector. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Bootstrapped standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, Bloomberg, Datastream, 2005 Q4 - 2014 Q4; author's calculations.

Table 2.21: *Covariance Risk-free Yield*

	Dependent variable: Netbuy					
	Funds		ICPF		Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔPrice	0.109***	0.153***	-0.928***	-0.363	0.539***	0.594***
	(0.035)	(0.040)	(0.174)	(0.233)	(0.126)	(0.137)
ΔPrice ∗ vol	-0.00240	-0.00925	0.0600	-0.0414	-0.121**	-0.130**
	(0.018)	(0.017)	(0.090)	(0.099)	(0.057)	(0.058)
R-squared	0.120	0.126	0.161	0.173	0.112	0.114
Observations	232321	232321	29848	29848	120336	120336
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes

The dependent variable is the change in the log of the nominal amount held. *ΔPrice* is the change in the log of the price and is lagged by one quarter. *vol* is the standard deviation of *ΔPrice*. *vol* is demeaned and standardized by the sample standard deviation. Column (1)-(2) estimate the specification for the investment fund sector. Column (3)-(4) estimate the specification for the insurance companies and pension fund sector. Column (5)-(6) estimate the specification for the banking sector. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Bootstrapped standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table 2.22: *Volatility*

	Dependent variable: Netbuy					
	Funds		ICPF		Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔPrice	0.0719***	0.133***	-1.003***	-0.463***	0.328***	0.346***
	(0.027)	(0.031)	(0.127)	(0.146)	(0.096)	(0.102)
VIX	0.00492		0.0464***		-0.00293	
	(0.003)		(0.012)		(0.007)	
ΔPrice ∗ VIX	0.140**	0.00936	0.623**	0.207	0.0888	0.0856
	(0.056)	(0.060)	(0.282)	(0.347)	(0.202)	(0.214)
R-squared	0.120	0.126	0.162	0.173	0.112	0.114
Observations	232041	232041	29848	29848	120283	120283
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes

The dependent variable is the change in the log of the nominal amount held. Δ*Price* is the change in the log of the price and is lagged by one quarter. *VIX* is the log of the implied volatility for S&P 500 stock options and demeaned by the sample average. Column (1)-(2) estimate the specification for the investment fund sector. Column (3)-(4) estimate the specification for the insurance companies and pension fund sector. Column (5)-(6) estimate the specification for the banking sector. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, Datastream, 2005 Q4 - 2014 Q4; author's calculations.

Table 2.23: *VIX*

	Dependent variable: Netbuy					
	(1)	(2)	(3)	(4)	(5)	(6)
ΔPrice	0.131^{*}	0.0540	0.109^{***}	0.106^{***}	0.0946^{*}	0.172^{***}
	(0.078)	(0.085)	(0.029)	(0.032)	(0.054)	(0.064)
R-squared	0.190	0.196	0.164	0.168	0.183	0.191
Observations	42186	42186	99962	99962	86831	86831
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes
Period	Pre-Crisis	Pre-Crisis	Crisis	Crisis	Post-Crisis	Post-Crisis

The dependent variable is the change in the log of the nominal amount held for investment funds. Δ*Price* is the change in the log of the price and is lagged by one quarter. *Pre-Crisis* refers to the period 2006 Q1:2008 Q1, *Crisis* refers to 2008 Q2:2012 Q3 and *Post-crisis* refers to 2012 Q4:2014 Q4. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table 2.24: *Crisis Split for Funds*

	Dependent variable: Netbuy					
	(1)	(2)	(3)	(4)	(5)	(6)
ΔPrice	-3.383***	-2.335***	-0.502***	-0.168	-0.466*	-0.531*
	(0.486)	(0.573)	(0.155)	(0.180)	(0.252)	(0.296)
R-squared	0.258	0.268	0.181	0.194	0.235	0.246
Observations	7776	7776	13225	13225	7877	7877
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes
Period	Pre-Crisis	Pre-Crisis	Crisis	Crisis	Post-Crisis	Post-Crisis

The dependent variable is the change in the log of the nominal amount held for insurance companies and pension funds. Δ*Price* is the change in the log of the price and is lagged by one quarter. *Pre-Crisis* refers to the period 2006 Q1:2008 Q1, *Crisis* refers to 2008 Q2:2012 Q3 and *Post-crisis* refers to 2012 Q4:2014 Q4. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table 2.25: *Crisis Split for ICPF*

	Dependent variable: Netbuy					
	(1)	(2)	(3)	(4)	(5)	(6)
ΔPrice	0.615**	0.664**	0.256**	0.302***	0.761***	0.569**
	(0.282)	(0.297)	(0.104)	(0.110)	(0.250)	(0.267)
R-squared	0.146	0.147	0.151	0.153	0.167	0.170
Observations	30665	30665	53165	53165	33314	33314
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes
Period	Pre-Crisis	Pre-Crisis	Crisis	Crisis	Post-Crisis	Post-Crisis

The dependent variable is the change in the log of the nominal amount held for banks. Δ*Price* is the change in the log of the price and is lagged by one quarter. *Pre-Crisis* refers to the period 2006 Q1:2008 Q1, *Crisis* refers to 2008 Q2:2012 Q3 and *Post-crisis* refers to 2012 Q4:2014 Q4. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table 2.26: *Crisis Split for Banks*

	Funds		ICPF		Banks	
Dependent variable:	Buy	Sell	Buy	Sell	Buy	Sell
	(1)	(2)	(3)	(4)	(5)	(6)
ΔPrice	1.592***	-0.524**	-0.865*	4.235***	1.825***	-1.232***
	(0.237)	(0.247)	(0.443)	(0.402)	(0.270)	(0.280)
R-squared	0.238	0.272	0.254	0.286	0.378	0.338
Observations	333827	336908	116917	119234	405185	408853
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable *Buy* is the log of the nominal amount bought. The dependent variable *Sell* is the log of the nominal amount sold. Δ*Price* is the change in the log of the price and is lagged by one quarter. Column (1)-(2) estimate the specification for the investment fund sector. Column (3)-(4) estimate the specification for the insurance companies and pension fund sector. Column (5)-(6) estimate the specification for the banking sector sector. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table 2.27: *Buy and Sell*

	Dependent variable: Netbuy					
	Funds		ICPF		Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Price$	0.121***	0.137***	-3.096***	-2.712***	0.875***	0.828***
	(0.037)	(0.039)	(0.682)	(0.662)	(0.276)	(0.276)
$\Delta Price*$ gov	-0.146**	-0.124*	2.442***	2.437***	-0.770**	-0.650**
	(0.069)	(0.070)	(0.698)	(0.673)	(0.310)	(0.309)
$\Delta Price *$ banks	0.0844	0.123*	2.406***	2.653***	-0.468	-0.446
	(0.069)	(0.071)	(0.718)	(0.695)	(0.300)	(0.299)
$\Delta Price *$ ofc	-0.0379	-0.0122	2.196***	2.246***	-0.293	-0.267
	(0.062)	(0.063)	(0.748)	(0.719)	(0.357)	(0.357)
R-squared	0.121	0.127	0.161	0.173	0.113	0.115
Observations	226726	226726	29556	29556	119033	119033
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes

The dependent variable is the change in the log of the nominal amount held. $\Delta Price$ is the change in the log of the price and is lagged by one quarter. *gov* is a dummy that equals one if the security is a government bond and zero otherwise. *banks* is a dummy that equals one if the security is a bank bond and zero otherwise. *ofc* is a dummy that equals one if the security is a bond issued by an other-financial institution and zero otherwise. The level coefficient reflects the response to non-financial corporate bonds. Column (1)-(2) estimate the specification for the investment fund sector. Column (3)-(4) estimate the specification for the insurance companies and pension fund sector. Column (5)-(6) estimate the specification for the banking sector. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table 2.28: *Issuer Sector Heterogeneity*

	Dependent variable: Netbuy		
	(1)	(2)	(3)
Specification	Funds	ICPF	Banks
(1) No Controls	0.156***	-0.461***	0.343***
	(0.021)	(0.113)	(0.070)
(2) Security FE	0.106***	-0.900***	0.351***
	(0.024)	(0.115)	(0.085)
(3) Macro Controls	0.140***	-0.792***	0.368***
	(0.024)	(0.116)	(0.085)
(4) Country Controls	0.172***	-0.828***	0.366***
	(0.024)	(0.121)	(0.087)
(5) Country∗Time FE	0.126***	-0.480***	0.345***
	(0.028)	(0.155)	(0.095)
(6) Country∗Sector∗Time FE	0.155***	-0.341**	0.387***
	(0.029)	(0.167)	(0.098)
(7) Sample of securities held by all	0.105***	-0.850***	0.341***
	(0.024)	(0.116)	(0.084)

The dependent variable is the change in the log of the nominal amount held. The coefficients are the estimated effect of ΔPrice. ΔPrice is the change in the log of the price and is lagged by one quarter. For each sector the number of observations are the same in specifications (1)-(6). *Macro Controls* include German GDP growth, inflation, the 10-year government bond yield for Germany and the EONIA as well as the VIX. *Country Controls* include country-specific GDP growth, inflation, the 10-year government bond yield for Germany and the EONIA as well as the VIX. Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, IMF, ECB, 2005 Q4 - 2014 Q4; author's calculations.

Table 2.29: *Summary Table*

	Dependent variable: Netbuy					
	Funds		ICPF		Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\text{Price}_{broad}$	-0.0142	0.0180	-1.125***	-0.463*	0.423***	0.537***
	(0.038)	(0.050)	(0.208)	(0.243)	(0.136)	(0.154)
$\Delta\text{Price}_{relative}$	0.127***	0.132***	-0.464***	-0.269*	0.342***	0.349***
	(0.028)	(0.029)	(0.148)	(0.152)	(0.096)	(0.097)
R-squared	0.116	0.122	0.162	0.173	0.109	0.111
Observations	207761	207761	27449	27449	108468	108468
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes

The dependent variable is the change in the log of the nominal amount held. $\Delta Price_{broad}$ is the price change of the index for the issuing sector in the specific country. $\Delta Price_{relative}$ is the deviation of the security-specific price change from the price change of the country-issuing sector index. All independent variables are lagged by one quarter. Column (1)-(2) estimate the specification for the investment fund sector. Column (3)-(4) estimate the specification for the insurance companies and pension fund sector. Column (5)-(6) estimate the specification for the banking sector. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table 2.30: *Broad and Relative Price Changes*

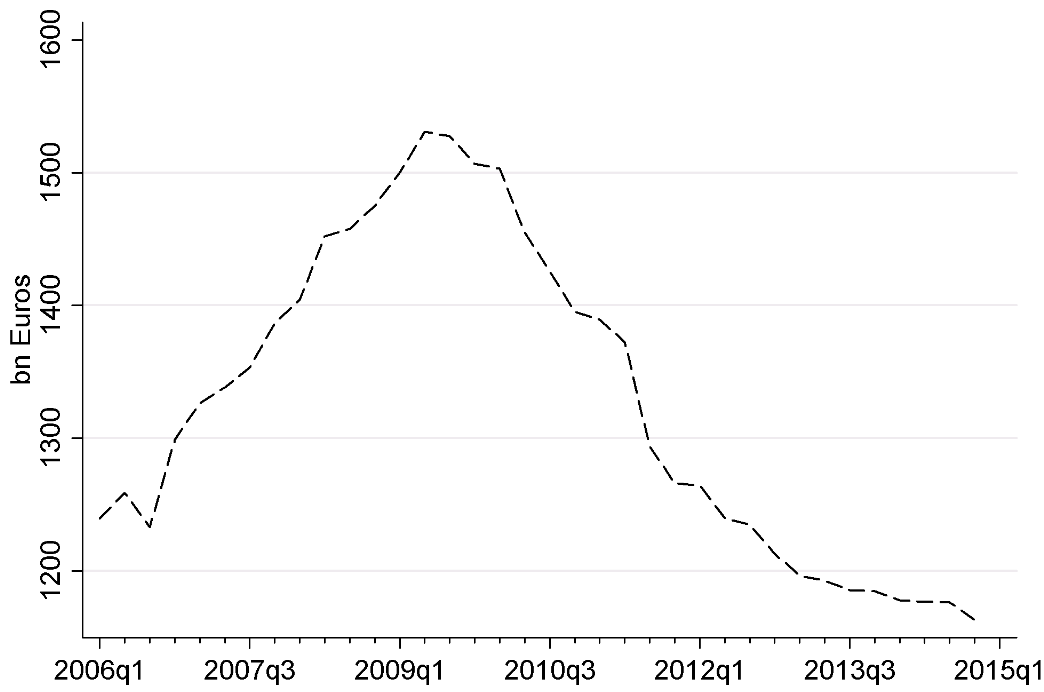

Figure 2.1: *Nominal Debt Security Holdings of Banks*

Note: The Figure shows the nominal value of debt securities held by banks. Source: Author's calculations; Data: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4.

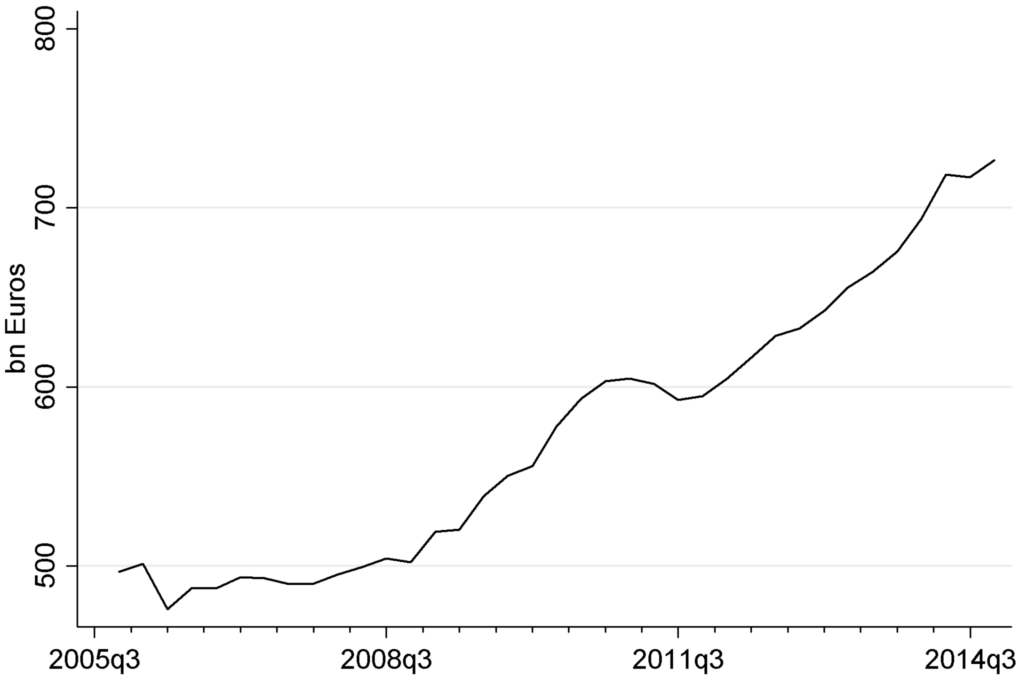

Figure 2.2: *Nominal Debt Security Holdings of Investment Funds*

Note: The Figure shows the nominal value of debt securities held by investment funds. Source: Author's calculations; Data: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4.

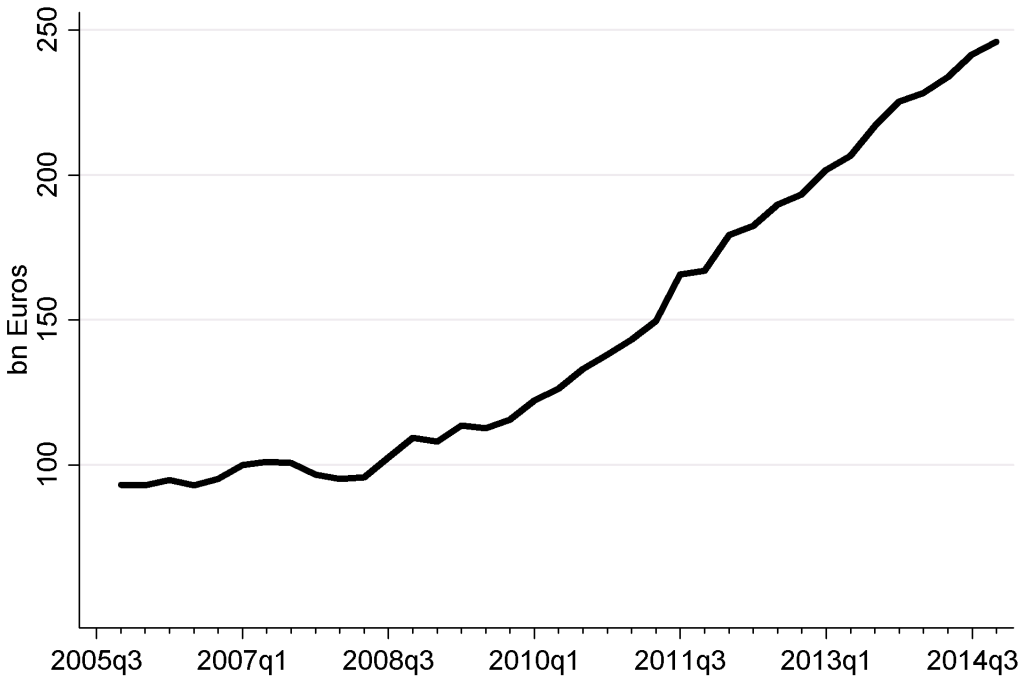

Figure 2.3: *Nominal Debt Security Holdings of Insurance Companies and Pension Funds*

Note: The Figure shows the nominal value of debt securities held by insurance companies and pension funds. Source: Author's calculations; Data: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4.

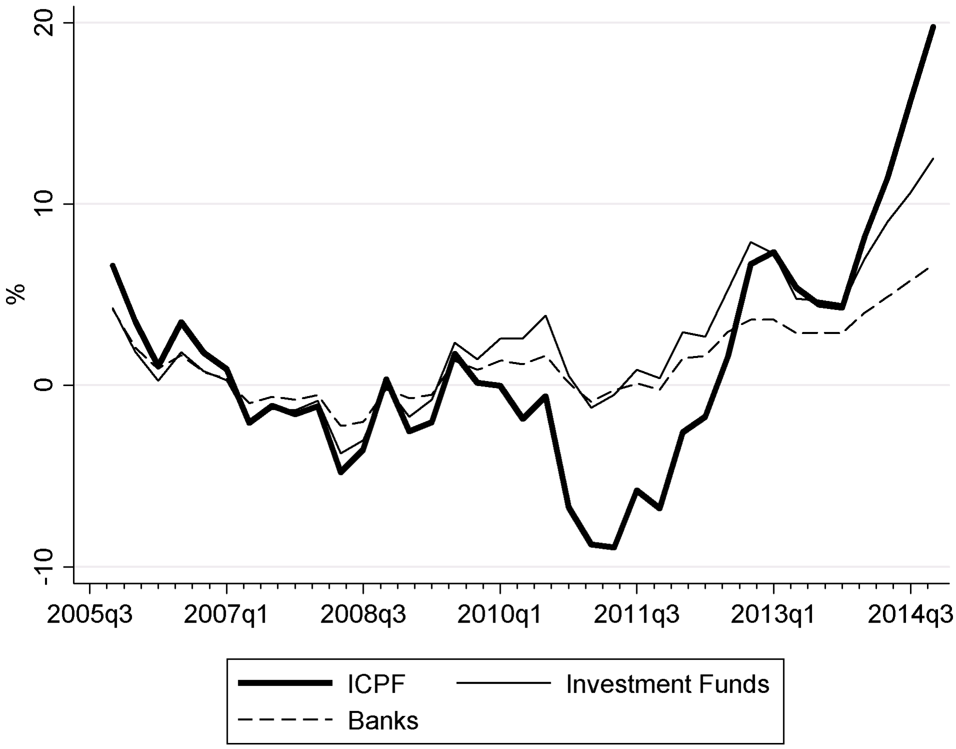

Figure 2.4: *Capital Gains on Security Holdings*

Note: The Figure shows the capital gains of *Banks*, *Investment Funds* and insurance companies and pension funds (*ICPF*). The capital gains are calculated as the difference between the total market value of all securities and the total nominal value of all securities divided by the total nominal value of all securities. Source: Author's calculations; Data: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4.

Figure 2.5: *Balance Sheet of Banks in Germany*

Note: Assets (in EUR billions, share of total assets): Loans to Non-Banks (3127, 40%), Loans to Banks (1950, 25%), Debt Securities (1176, 15%), Others (1599, 20%); Liabilities (in EUR billions, share of total liabilities): Capital (382, 5%), Retail Deposits (3299, 42%), Interbank Borrowing (1717, 22%), Debt Securities issued (1115, 14%), Other (1341, 17%); Total: EUR 7853 billion. Source: Author's calculations; Data: Deutsche Bundesbank, time series database, banks and other financial institutions, banks.

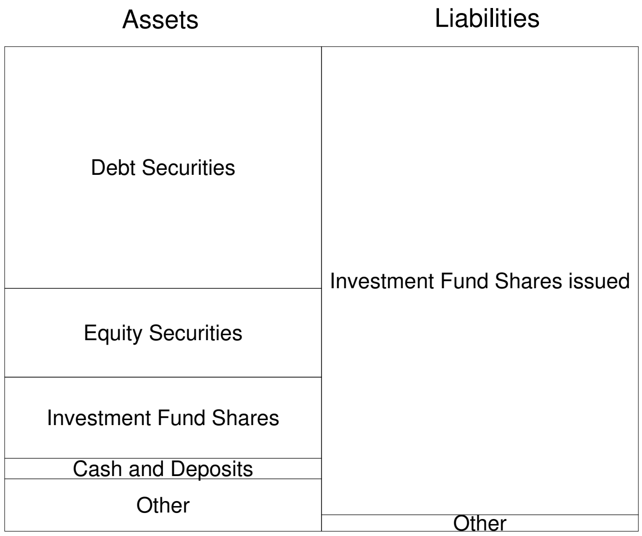

Figure 2.6: *Balance Sheet of Investment Funds in Germany*

Note: Assets (in EUR billions, share of total assets): Debt Securities (825, 50%), Equity Securities (303, 18%), Investment Fund Shares (277, 17%), Cash and Deposits (70, 4%), Other (179, 11%); Liabilities (in EUR billions, share of total liabilities): Investment Fund Shares issued (1597, 97%), Other (56, 3%); Total: EUR 1653 billion. Source: Author's calculations; Data: Deutsche Bundesbank, time series database, banks and other financial institutions, investment companies

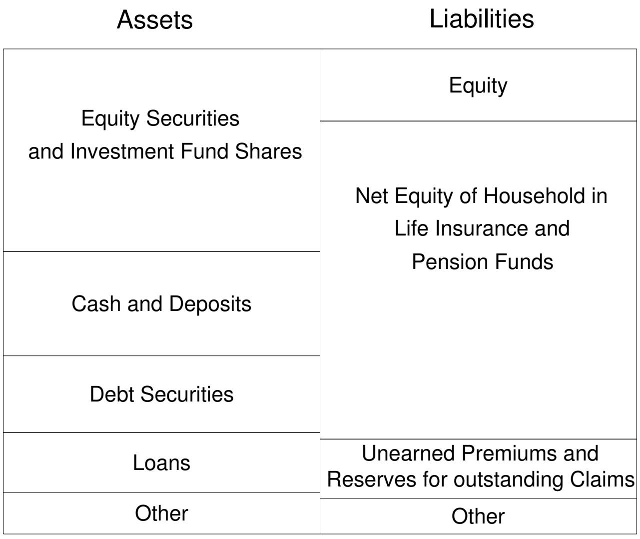

Figure 2.7: *Balance Sheet of Insurance Companies and Pension Funds in Germany*

Note: Assets (in EUR billions, share of total assets): Investment Fund Shares and Equity Securities (1014, 42%), Cash and Deposits (384, 21%), Debt Securities (384, 16%), Loans (299, 12%), Other (209, 9%); Liabilities (in EUR billions, share of total liabilities): Equity (361, 15%), Net Equity of Household in Life Insurance and Pension Funds (1592, 66%), Unearned Premiums and Reserves for outstanding Claims (296, 12%), Other (90, 3%) Total: EUR 2428 billion. Source: Author's calculations; Data: Deutsche Bundesbank, time series database, banks and other financial institutions, insurance corporations and pension funds.

Appendix

While most securities have a constant amount outstanding over time, the supply of some securities can change. The actual amount outstanding can change if the bond is callable or when for asset-backed securities a part of the amount issued is returned to investors early. The effective amount outstanding (the tradable amount) of securities can for instance be altered when securities are bought under asset-purchase programs. While if the total amount outstanding diminishes, the security is not included in the sample, the security is included when the amount outstanding is not reduced to zero. In order to make sure that the changed amount outstanding does not appear as a transaction, I adjust by the pool-factor.[54]

The nominal value is

$$NominalValue = RawValue * e * Poolfactor \tag{2.16}$$

where e is the domestic price of foreign currency. The pool factor adjusts the nominal value of the specific security by partial or special redemptions. If no redemption has occurred, the poolfactor is one. It gives the amount that is left to be distributed.

In order to obtain a nominal value that moves only when a security is actually bought or sold, the nominal value needs to be adjusted by exchange rate changes and the pool factor.

$$AdjustedNominalValue_t = \frac{NominalValue_t}{Poolfactor_t} * \frac{e_{t-1}}{e_t} \tag{2.17}$$

$\frac{e_{t-1}}{e_t} - 1$ is the percentage appreciation of the Euro. If the Euro appreciates and the foreign currencies depreciate, this reduces the nominal value of securities in Euros if these securities are denominated in foreign currency and these movements do not reflect buy decisions. By multiplying by the poolfactor, I adjust for partial or special redemptions. In the text, I always refer to the adjusted nominal value in order to adjust for the movements that do not reflect investment decisions. The netbuy variable is obtained by taking the natural log change of the adjusted nominal value given they trade.

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[54] This changed supply can still have effects that are not captured by the security fixed effects. However, I can control for this security-specific amount outstanding by including security∗time fixed effects.

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Chapter 3

Discriminatory Pricing of over-the-counter Derivatives[1]

[1]Co-authored with Harald Hau, Peter Hoffmann and Sam Langfield.

3.1 Introduction

At the G20 summit in Pittsburgh in 2009, governments agreed that all standardized over-the-counter (OTC) derivatives contracts should be centrally cleared and traded on exchanges or electronic trading platforms. Yet this international agreement has been only partially implemented (Financial Stability Board, 2016). Relative to interest rate and credit derivatives, reform of the market for foreign exchange (FX) derivatives has fallen particularly short of the Pittsburgh agenda (Duffie, 2011).[2] This paper evaluates the implications of the current OTC market structure for non-financial firms. We document extensive discriminatory pricing by dealers with respect to their non-financial clients, analyze the determinants of price discrimination, and quantify the effect of request-for-quote (RFQ) multi-dealer electronic trading platforms on lowering spreads. Our analysis is relevant for the regulation of FX derivatives markets, which have hitherto been subject to little academic inquiry, despite their large size and importance for both the financial sector and the real economy.

The FX derivatives market provides a rich setting in which to study discriminatory pricing. This market features significant participation by non-financial firms; unlike participants in other OTC markets, these firms are heterogeneous in their financial sophistication, ranging from large multinational corporations to small import-export firms. Anecdotal evidence from the industry suggests that some clients simply do not know whether the spreads they pay are competitive—an information deficit that dealers could exploit to their advantage.[3] At the same time, participation in the FX derivatives market is important for firms' risk management. The consequences of inadequate currency risk management were demonstrated recently by Monarch, a UK-based airline, which filed for bankruptcy in part owing to the depreciation of sterling (in which much of its revenues were denominated) against the US dollar (the invoice currency for expenses such as fuel and aircraft).[4]

[2] In both the US and the EU, certain interest rate and credit derivatives are now subject to mandatory central clearing and an obligation for trading to occur on organized trading platforms. By contrast, FX derivatives markets are not subject to these requirements.

[3] See, for example, "Many SMEs fail to grasp foreign exchange risk", *Financial Times*, September 26, 2013, available at: https://www.ft.com/content/338d3d5a-269c-11e3-bbeb-00144feab7de.

[4] In a media interview following Monarch's bankruptcy, the newly appointed administrator referred to the "very material impact" arising from the exchange rate movement of sterling against the US dollar (see "Monarch Airlines goes bust", Reuters, October 2, 2017, available at: https:

Our analysis draws on new data available under the European Market Infrastructure Regulation (EMIR), which forms the largest transaction-level dataset on derivatives available globally. In this dataset, we observe the identity of both counterparties to each trade, as well as the contract characteristics. Focusing on EUR/USD forward contracts executed between April 1, 2016 and March 31, 2017, we analyze approximately half a million trades between 204 dealers and 10,062 of their non-financial clients. For each transaction, we compute the spread as the difference between the contractual forward rate and the mid-price from Thomson Reuters Tick History (TRTH). This allows us to compare execution quality across clients, conditional on contract characteristics.

We obtain four main findings. First, transaction spreads across clients are highly heterogeneous. Conditional on contract characteristics, dealer fixed effects, and market conditions, the client at the 75th percentile of the spread distribution pays an average of 30 pips over the market mid-price. This compares to competitive spreads of less than 2.5 pips paid by the bottom 25% of clients.

What accounts for this high dispersion in spreads? Our second finding is that less sophisticated clients— those with fewer counterparties, lower annual trading volumes, and fewer FX and non-FX contracts—pay substantially higher average spreads for the same contracts than more sophisticated clients. These proxies of client sophistication account for approximately 20% of the variation in average client spreads spanned by client fixed effects. The existing OTC market structure therefore subjects unsophisticated clients to substantial rent extraction by their dealers. This is consistent with search models such as Duffie et al. (2005), which predict that transaction costs decrease with client sophistication.

Third, we explore the effect of multi-dealer RFQ platforms. These platforms allow clients to request quotes from multiple dealers simultaneously. We find that trades which are executed via RFQ platforms feature competitive spreads, regardless of the sophistication of the client operating on the platform. This finding suggests that the use of more centralized electronic trading can eliminate the discriminatory pricing that exists in the current market structure.

Fourth, we find evidence that dealers are able to extract information rents. The OTC FX derivatives market is opaque, since there is no centralized dissemination of transaction prices. Consequently, dealers' superior information on prices puts them at an advantage relative to clients, for which information collection is more

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costly. Dealers exploit this information advantage by not passing on recent changes in the mid-price that would otherwise be to the benefit of the client. Interestingly, these information rents are not observed for trades on multi-dealer RFQ platforms.

We explore three further hypotheses that could account for variation in average client spreads. First, the *Relationship Hypothesis* posits that trades between clients and dealers with established relationships occur at more favorable forward rates. Yet we find no evidence that client-dealer relationships are associated with lower spreads; instead, we find some evidence for higher spreads. Second, the *Credit Risk Hypothesis* predicts that less creditworthy clients pay higher spreads. Changes in the market value of FX forwards can lead to counterparty credit risk. However, we find no evidence that client credit risk affects the pricing of FX forwards. Finally, the *Customization Hypothesis* suggests that non-standard contracts should trade at higher spreads. We measure customization as the distance in days between contracted maturity and the closest standard maturity, and indeed find that more non-standard maturities command higher spreads.

Related Literature

Our work contributes to the literature on OTC markets. In these markets, prospective counterparties must search for trading opportunities (Duffie et al., 2005).[5] Moreover, OTC markets are typically opaque as price information is not disseminated publicly, either before or after trade execution (Duffie, 2012). These frictions—namely search costs and opacity—give rise to imperfect competition. If these frictions are heterogeneous across OTC market participants, discriminatory pricing emerges as an equilibrium outcome.

Previous empirical studies provide some evidence regarding price variation in other OTC markets. Early contributions document that spreads are decreasing with trade size (see, for example, Schultz (2001), Harris and Piwowar (2006) and Green et al. (2007) for evidence on bond markets). More recently, O'Hara et al. (2018) examine the spreads paid by insurance companies trading corporate bonds, and find that more active insurance companies receive better prices for corporate bonds compared to less active insurers. In the FX spot market, Osler et al. (2016) use transaction data from a single bank to show that non-financial firms pay larger spreads than institutional investors. By contrast, the focus of our analysis is on

[5]Extensions of this canonical search model include Duffie et al. (2007) and Lagos and Rocheteau (2007, 2009).

heterogeneous execution quality within the group of non-financial firms.

The transaction data used in prior empirical studies typically do not identify counterparties, which limits inference about the determinants of price discrimination. In addition, most OTC markets, notably the bond market, are dominated by institutional investors, where even relatively small market participants are reasonably sophisticated investors, whose primary expertise relates to the market in which they operate. In contrast, many of the clients trading FX derivatives are financially unsophisticated. This renders them susceptible to price discrimination.

Another strand of the literature uses event studies to examine the effect of OTC bond market transparency on execution quality. Bessembinder et al. (2006), Goldstein et al. (2006) and Edwards et al. (2007) document that higher post-trade transparency in US corporate bond markets after the introduction of the Trade Reporting and Compliance Engine (TRACE) in 2002 generally reduced transaction costs and increased liquidity. Public transaction records allow clients to verify the execution quality of their trades, thereby mitigating information asymmetries.

In spite of their considerable size, derivatives markets have been subject to little empirical analysis. A notable exception is Loon and Zhong (2014, 2016), who examine the effect of centralized clearing and enhanced post-trade transparency in the CDS market, and find positive effects on market liquidity In addition, Benos et al. (2016) analyze interest rate swap transactions recorded by the London Clearing House (LCH). They find that pre-trade transparency due to mandatory execution in Swap Execution Facilities (SEFs) increased market liquidity and lowered transaction costs. However, their data do not allow for the identification of individual market participants, and thus cannot shed light on the relationship between counterparty characteristics and price discrimination. Also related to our paper, Du et al. (2016) examine counterparty risk in CDS and show that it is priced, although the economic magnitude is small.

Our paper also relates to the literature on corporate hedging. Nance et al. (1993) argue that larger clients are more likely to hedge their currency risk because they benefit from scale economies of market participation. Yet the source of these scale economies is not elucidated. Guay and Kothari (2003) also show that larger clients engage more in derivatives activities, but that the magnitude of their positions tends to be small. Our analysis sheds light on these results: we document that more sophisticated clients with superior scale economies generally pay lower spreads.

3.2 Hypotheses

In this section, we articulate six hypotheses about the determinants of spreads on FX derivatives. Our first hypothesis relates to the theoretical literature on OTC markets. Duffie et al. (2005) show that dealers charge lower mark-ups to more sophisticated clients. In their model, clients with better (or faster) access to alternative dealers pay lower transaction costs. Intuitively, the ability to turn quickly to another counterparty exposes dealers to "sequential competition", inducing them to offer more competitive spreads. In addition, some clients have more bargaining power than others, resulting in better terms of trade. For example, larger trades are more profitable to dealers and can therefore results in price concessions. Also, some clients can devote more resources to eliminating the informational advantage of dealers, for example by purchasing real-time data feeds. We summarize these arguments in the following hypothesis.

> **Hypothesis 1: Client Sophistication**
> More sophisticated clients trade at lower spreads.

Besides client sophistication, the trading mechanism can matter for execution quality. Traditionally, most FX forwards were negotiated bilaterally, elevating search costs for all prospective clients. More recently, the advent of electronic trading has given rise to platforms on which clients can request quotes from multiple dealers simultaneously. Evidence from other markets suggests that such RFQ platforms reduce search costs, forcing dealers to compete with each other (Flood et al., 1999; Hendershott and Madhavan, 2015). We therefore expect that the use of RFQ platforms is associated with a reduction in spreads. In addition, we expect that the least sophisticated clients see the largest decrease in spreads, as they have the most to gain from a more competitive trading environment. This gives rise to our second hypothesis:

> **Hypothesis 2: RFQ Platforms**
> Trades executed via RFQ platforms exhibit lower spreads. The spread reduction is larger for less sophisticated clients.

OTC markets are opaque, and sometimes referred to as "dark markets" (Duffie, 2012). Unlike in centralized markets, there is typically no obligation for dealers to disclose prices or quotes publicly. Freely available real-time mid-prices are not available for FX forwards. This gives rise to an information asymmetry between dealers and clients. While dealers can infer price information from their frequent interactions in inter-dealer and dealer-to-client markets, clients are generally less well informed about the prevailing mid-price, particularly after sudden price movements.[6] Therefore, we expect dealers to earn information rents around mid-price changes through an asymmetric price adjustment. Consider for example a dealer that is approached by a client just after the EUR/USD forward rate has increased. For a client buy order, the dealer will base its quote on the updated market price. However, for a client sell order, the dealer has an incentive to offer a quote based on the outdated lower price. The opposite is true for trades following price decreases (i.e. the dealer will be tempted to quote based on the outdated higher price in case of a client buy order). Taken together, client orders in the opposite direction of recent price changes are predicted to incur higher spreads compared to trades in the same direction. Such asymmetric price adjustment is common in retail markets (see, e.g., Peltzman, 2000), and has also been documented for smaller trades in the US municipal bond market (Green et al., 2010). Moreover, we can test whether these information rents are reduced or even eliminated through enhanced competition on RFQ platforms.

> **Hypothesis 3: Information Rents**
> Dealers earn information rents through asymmetric price adjustment. Client orders in the opposite direction of recent price changes incur higher spreads than trades in the same direction. Multi-dealer RFQ platforms reduce these information rents.

Empirical research on trading networks highlights that most market participants concentrate their trading in relatively few counterparties.[7] Consistent with preferential treatment, Cocco et al. (2009) document relationship discounts in the Portuguese interbank market. In a similar vein, Hendershott et al. (2017) develop and test a model where dealers grant better prices to relationship clients to retain

[6] One way to reduce information frictions is to publish benchmark prices, which are available for a number of OTC markets. Duffie et al. (2017) show how the use of such benchmarks can raise welfare.

[7] See Cocco et al. (2009) and Afonso et al. (2013) for evidence regarding the overnight interbank market; Hendershott et al. (2017) and Di Maggio et al. (2017) for the corporate bond market; and Abad et al. (2016) for three different derivatives markets, including FX.

future business. Di Maggio et al. (2017) study a large dealer in the US corporate bond market and show that existing relationships are not easily substitutable. These insights motivate our fourth hypothesis.

Hypothesis 4: Client-Dealer Relationships

Client-dealer relationships are associated with lower spreads.

Next, we consider the role of counterparty credit risk in the pricing of FX derivatives. The bilateral nature of these transactions exposes counterparties to counterparty credit risk. However, in CDS markets, Arora et al. (2012) and Du et al. (2016) find that the role of counterparty risk in the pricing of contracts is extremely low. Despite this, the exemption of FX derivatives from central clearing requirements can imply that there remains a role for counterparty credit risk in these markets (Duffie, 2017). The absence of central clearing from FX derivatives markets provides the foundation for our fifth hypothesis:

Hypothesis 5: Client Counterparty Risk

Clients with higher counterparty credit risk incur higher spreads.

The International Swap and Derivatives Association (ISDA) has defended the OTC market structure of derivatives markets as a way of providing customized contracts that are tailored to clients' needs (see, for example, ISDA (2010) and Duffie et al. (2010)). One dimension along which FX forwards can be customized is their maturity. By contrast, exchange-traded futures only provide specific maturities, so they can expose risk managers to undesirable basis risk. Accordingly, clients can be willing to incur larger spreads for customized contracts. Further, non-standard tenors render price comparisons with published benchmark rates more difficult, which may allow dealers to earn larger information rents. This gives rise to our final hypothesis:

Hypothesis 6: Contract Customization

Forward contracts with more customized maturities trade at higher spreads.

3.3 Data and Measurement

3.3.1 Data Sources

At the Pittsburgh summit in September 2009, G20 leaders determined that OTC derivatives contracts should be reported to regulators. In the European Union (EU), this commitment is implemented in the European Markets Infrastructure Regulation (EMIR). Since February 2014, all counterparties resident in the EU have been required to report the contractual details of new and outstanding derivatives transactions to trade repositories, which share the data with authorities according to their jurisdiction. Two institutions, namely the European Systemic Risk Board (ESRB) and European Securities and Markets Authority (ESMA), have access to the full EU-wide transaction-level dataset, which is described in detail by Abad et al. (2016).

We obtain transaction-level data on all OTC FX derivatives transactions involving at least one EU counterparty. We focus on forwards referenced on EUR/USD, which constitute the obligation to buy or sell a given quantity of euro against dollar at a predetermined rate of exchange at some future date.[8] Our data cover both outright forwards and the forward leg of an FX swap. According to the Bank for International Settlements, these contract types account for approximately 85% of all FX derivatives, and EUR/USD is the currency cross with the largest notional outstanding (BIS, 2017).

Starting with the raw data obtained from trade repositories, we retain all trades marked as FX forwards in the EUR/USD currency pair with a maturity up to one year. Our sample period covers trades executed between April 1, 2016 and March 31, 2017. The transaction records provide a unique legal entity identifier for all counterparties, which allows us to match the transactions data to Bureau van Dijk's Orbis dataset. From Orbis, we retrieve information on counterparties' sector classification. Given our focus on discriminatory pricing, we retain trades in which one counterparty is classified as a non-financial firm and the other as a dealer (including both broker-dealers and banks). The final transaction-level dataset comprises 556,297 trades between 10,062 clients and 204 dealers. Summary statistics are reported in Table 3.1.

[8]For example, a client which sells a 3-month EUR/USD forward with a notional of Euro 1 million and a forward rate of 1.2 agrees to transfer Euro 1 million to a dealer in three months' time in exchange for $1.2 million, regardless of the spot rate prevailing on the settlement date.

3.3.2 Measuring Transaction Spreads

We assess transaction costs by computing the effective spread (henceforth "spread")—that is, we compare the forward rates of executed trades to the competitive market mid-price at the corresponding tenor. For the latter, we use Thomson Reuters Tick History (TRTH) data, which combine two-sided intraday quotes from multiple dealers. These high-frequency quote data are available for forward rates at standard maturities of 1 day, 1 week, 2 weeks, 3 weeks, 1 month, 2 months, 3 months, 6 months, and 1 year. For each of these maturities, we compute the market mid-price from the best inside quotes of the participating dealers. To avoid using stale quotes, we assume that indicative quotes are valid for a maximum of 30 seconds. As our derivatives data are time-stamped to the full second, the mid-price is calculated from all valid quotes in the same second.

OTC trading allows for contract customization. Consequently, tenors vary significantly across the 556,297 trades in our dataset, as shown in Figure 3.1. To match contractual forward rates at non-standard maturities to the nine standard maturities for which we have mid-price data, we linearly interpolate across the nine standard maturity dates. For example, the mid-price for a 10-day forward is calculated as the weighted average of the 1-week and 2-week mid-prices, where the weights are 3/7 and 4/7, respectively.

To assess the quality of the mid-prices, we compare for each full trading hour the forward rates of all inter-dealer trades (on which EMIR also provides full information) to their corresponding contemporaneous mid-prices at the same matched maturity. The mean (median) difference between these variables is just 0.138 pips (-0.01 pips), with a standard deviation of 5.27 pips. This suggests that the calculated mid-prices approximate inter-dealer trades very closely, and thus constitute a reliable benchmark price.

The spread for each client-dealer trade is measured relative to the mid-price at the corresponding maturity. Let d_τ denote the direction of client orders, so $d_\tau = 1$ for client long positions in a EUR/USD forward ("client buys euro"), and $d_\tau = -1$ for short positions ("client sells euro"). The spread (expressed in pips) for transaction τ is defined as

$$Spread_\tau = d_\tau \times (f_\tau - m_\tau) \times 10^4,$$

where f_τ is the contractual forward rate, and m_τ the contemporaneous mid-price, interpolated linearly from the mid-prices of standard maturities. For example, if a client buys euro at 1.0500, but the prevailing mid-price is 1.0450, the spread paid by the client is 50 pips. To further illustrate this spread calculation, Figure 3.2 plots contractual forward rates against the mid-price for 1-month forwards executed on a given trading day.

3.3.3 Variables for Hypothesis Testing

The first hypothesis concerns client sophistication. Empirically, we measure sophistication in five ways. First, we define $Log\#Counterparties$ as the natural logarithm of the number of dealers with which a client trades over one year. This variable relates to the parameter ρ in Duffie et al. (2005), which denotes the intensity with which investors meet dealers. Clients with a high ρ, as proxied by a high $Log\#Counterparties$, meet dealers more frequently, exposing them to "sequential competition". We alternatively capture the size of a client's set of counterparties via the Herfindahl-Hirschman index (denoted HHI) of its trading volume across different dealers. This measure is expected to be inversely related to $Log\#Counterparties$, as higher dealer concentration implies that a client has fewer counterparties. Further, we calculate $LogTotalNotional$ as the log of total notional (in euros) of all EUR/USD forwards traded by a client in our one-year sample period. Clients with higher trading volumes are more likely to spend resources in searching for competitive spreads. In addition, their larger trading volumes make them more attractive clients for dealers. Both effects improve the bargaining power of clients in bilateral negotiations, as captured by the parameter z in Duffie et al. (2005). Similarly, we define $Log\#TradesFX$ as the log of the number of EUR/USD forwards traded by a client in our one-year sample period. Finally, $Log\#TradesNonFX$ is the log of one plus the total number of a client's outstanding positions in interest rate, credit, and commodity derivatives at the start of our sample period on April 1, 2016. Trading experience in other derivatives contracts proxies for client sophistication in a similar way to $Log\#TradesFX$, but is not directly related to the spreads paid by clients in FX forwards. In our later analysis, it is useful to collapse these five measures of client sophistication into a single variable. To do this, we define $Sophistication$ as the first principal component of these variables. We obtain qualitatively and quantitatively similar results if we instead calculate a linear combination of the respective regression fits of these variables.

The second hypothesis concerns the role of multi-dealer RFQ platforms. Our transaction-level data allow us to identify trades that were conducted via one of the four major multi-dealer RFQ platforms in the European FX market, namely 360t, FXall, Bloomberg, and Currenex. Accordingly, we define a dummy variable, $RFQPlatform$, that is equal to one for trades executed via these platforms, and zero otherwise. In later regressions, we interact the $RFQPlatform$ dummy with the aforementioned summary measure of client sophistication, i.e. $Sophistication$, to identify how the effect of platform trading on transaction spreads varies across clients.

Hypothesis 3 relates to dealer information rents. In order to identify whether dealers adjust prices asymmetrically following changes in the mid-price, we define $|\Delta m_\tau^{-d}|$ ($|\Delta m_\tau^{d}|$) as the absolute value of the change in the mid-market forward rate over the preceding 30 seconds (in pips) if the price change was in the opposite (same) direction than the client order, and zero otherwise. More formally,

$$\begin{aligned}
|\Delta m_\tau^{-d}| &= \begin{cases} |\Delta m_\tau| & \text{if } sign(d_\tau) \neq sign(\Delta m_\tau) \\ 0 & \text{otherwise} \end{cases}, \\
|\Delta m_\tau^{+d}| &= \begin{cases} |\Delta m_\tau| & \text{if } sign(d_\tau) = sign(\Delta m_\tau) \\ 0 & \text{otherwise} \end{cases},
\end{aligned}$$

where Δm_τ denotes the market mid-price change in the 30-second interval prior to trade τ. Hypothesis 3 predicts that the coefficient of $|\Delta m_\tau^{-d}|$ is positive, while the coefficient of $|\Delta m_\tau^{+d}|$ is expected to be zero. Interacting both variables with the $RFQPlatform$ dummy reveals how the use of RFQ platforms affects dealers' information rents.

Fourth, we evaluate the effect of client-dealer relationships on spreads. We measure client-dealer relationships in two distinct ways. First, we define $Notional_{i,d}/Notional_i$ and $Notional_{i,d}/Notional_d$, which is the notional traded in EUR/USD forwards between client i and dealer d relative to their respective total notionals traded. Such measures are frequently used in the literature to test the effect of relationships on trading terms (Cocco et al., 2009). However, they are endogenous and specific to the data sample. Our second measure captures the existence of bilateral credit relationships outside the FX market, which is arguably unrelated to derivatives trading. To this end, we retrieve the identities of firms' main relationship banks from Orbis (via a variable called "banker"). We then create a dummy variable, $Relationship$, that takes the value of one for trades where the dealer is engaged in a pre-existing credit relationship with the client, and zero otherwise.

Fifth, to measure a client's credit risk, we use the modified Altman credit score ($ZScore$), which is computed as a linear combination of working capital, retained earnings, profits, and sales.[9] As an alternative measure of client credit risk we use the volatility of its cash flows (*CashFlowVol*). The underlying data are obtained from Orbis.

Our final hypothesis concerns contract customization. We define $LogCustomization$ as the log of one plus $Customization$, which is the absolute value of the difference (in days) to the nearest standard tenor published by WM/Reuters.[10] As customization represents an alternative explanation for the observed heterogeneity in spreads, we generally include it as a control variable in all specifications.

3.4 Descriptive Statistics

Table 3.1, Panel A provides summary statistics on the 10,062 clients trading with dealers in the EUR/USD FX forward market for the sample period between April 1, 2016 and March 31, 2017.

A key variable of interest is the average spread paid by a client over all its trades ($Av.ClientSpread$). The mean value of $Av.ClientSpread$ in the sample is 18.1 pips, with a large standard deviation of 26.6 pips. The distribution of this variable is positively skewed, and clients at high percentiles pay very considerable spreads. For example, the client at the 75th percentile pays an average spread of 33.9 pips, while the clients and the median and 25th percentile pay 14.3 pips and 2.0 pips, respectively. This is illustrated in Figure 3.3, which plots the cross-sectional distribution for the 10,062 average spreads at client level using a kernel estimator. The high dispersion in average client spreads is suggestive of substantial price discrimination.

Further, we observe that a large fraction of clients in the sample have only few counterparties. More than half of clients trade with just one dealer. Even the client at the 75th percentile of the $\#Counterparties$ distribution has just two counterparties. This counterparty concentration is also reflected in HHI, which

[9] The formula to calculate the modified Altman $ZScore$ is: $1.2 \times WorkingCapital + 1.4 \times RetainedEarnings + 3.3 \times EBITDA + 0.999 \times Sales$, where all variables are scaled by total assets.

[10] The standard maturities are: O/N, T/N, 1W, 1M, 2M, 3M, 6M, 9M, 1Y. See https://financial.thomsonreuters.com/content/dam/openweb/documents/pdf/financial/wm-reuters-methodology.pdf for details.

measures the degree of concentration of a client's dealer trading relationships. Clients with a low HHI have diverse trading relationships; clients with a HHI of 1 have only one dealer as their counterparty. The average HHI is 0.8, with just over half of clients having a HHI of one.

On average, clients traded a total notional of Euro2.7mn over the one year sample period. However, the heterogeneity in trading volumes is very large, with clients at the 10th and 90th percentiles of the distribution trading approximately Euro$100,000$ and Euro120 million, respectively. A similar picture emerges from the variables *#TradesFX* and *#TradesNonFX*, which respectively measure clients' trading frequency in FX and non-FX derivatives markets.

Turning to client-dealer relationship variables, we aggregate *Relationship* at the client level and observe that on average clients trade about 60% of their FX forwards with their relationship bank(s). The summary statistics indicate a bimodal distribution of this variable: while at least 25% of clients never trade with their relationship bank(s), more than 50% exclusively trade with their relationship bank(s).

The final two variables reported in Table 3.1, Panel A measure clients' credit risk. *ZScore* represents the modified Altman Z-Score. The lower the *ZScore*, the riskier the client.[11] On average, clients in our sample have a *ZScore* of 2.9, which is above the average of 1.9 reported in Campello et al. (2011). In addition to the *ZScore*, we consider clients' cash flow volatility (*CashFlowVol*), which we standardize to have a zero sample mean and unit sample variance.

Next, we turn to the number of trades executed by each client. While the median client trades 10 times during our sample period, the mean trade count is 61.7, driven by a small number of clients that trade very frequently. For example, the client at the 90th percentile of the distribution trades 103 times in our 12-month sample. In contrast, the client at the 25th percentile trades only three times. Thus, our sample of 10,062 clients is comprised of a large number of small entities that trade FX forwards infrequently, and a small number of very active traders.

Table 3.1, Panel B provides summary statistics at the transaction level for the $556,297$ EUR/USD forward trades. The distribution of spreads is much narrower compared to the one obtained at client level. The average spread over all trades is only 6.6 pips, compared to 18.1 pips across clients. The spread at the 90th

[11] According to Altman (1968), a client that has a *ZScore* of greater than 2.9 is considered to be in the "safe" zone; clients with a *ZScore* of greater than 1.23 and smaller than 2.9 are in the "gray zone"; and clients with a *ZScore* of less than 1.23 are in the "distressed" zone.

percentile of the transaction-level distribution is 30.4 pips, compared to 52.6 pips at the client level. This suggests that more active traders obtain lower transaction costs on average. Moreover, we see that the spread at the 25th percentile of the transaction-level distribution is slightly negative, at -1.2 pips, compared with a positive average client spread at the same percentile. The existence of negative spreads is consistent with evidence from dealer-client segments in other OTC markets, such as the sovereign bond market (Dunne et al., 2015). Transactions with a negative spread can occur when dealers engage in price shading in order to rebalance their inventories (Garman, 1976; Amihud and Mendelson, 1980).

Most contracts have an underlying notional value of less than Euro1 million; just under 10% of contracts have a notional in excess of Euro15 million. On average, trades have a tenor that is approximately five days from the nearest standard tenor. Half of all transactions pertain to contracts with an original maturity of fewer than 35 days. The frequency of executed trades is decreasing as a function of the tenor of the contract, as shown in Figure 3.1.

The table also reports the distribution of Buy, which is a dummy equal to one when a client commits to buy euros against dollars (taking a long position in EUR/USD), and zero for sell-euro positions. In 40% of all trades in our sample, clients enter a long position, so that the value of the position is positive when the euro appreciates.

$RFQPlatform$ is a dummy equal to one if a transaction was executed via a multi-dealer RFQ platform, and zero otherwise. Approximately 40% of trades in our sample are executed through such trading platforms, which is broadly in line with existing survey evidence on the use of multi-dealer platforms (see BIS, 2016). Finally, we observe that the means of $|\Delta m_\tau^{-d}|$ and $|\Delta m_\tau^{+d}|$ are both 0.5 pips, indicating that the average price change preceding client orders in the preceding 30 seconds is very small.

3.5 Analysis

To analyze the determinants of transaction spreads, we estimate a linear model for the 556,297 client-dealer trades in our sample. The baseline specification takes the form:

$$Spread_{i,d,\tau} = X_i\beta_1 + Z_\tau\beta_2 + \delta_d + \gamma_t + \gamma_m + \epsilon_\tau,$$

where X_i represents client characteristics, and Z_τ a set of contract characteristics. Additionally, we include dealer fixed effects (δ_d) in all specifications to control for time-invariant dealer-specific characteristics. In this way, we compare the spread that a dealer charges to one client with the spread that the same dealer charges to another client. Omitted variables at the dealer level therefore do not affect our inference. To control for time-varying market conditions, we include date (γ_t) and minute-of-day (γ_m) fixed effects. The contract characteristics comprise the following transaction controls:

$$Z_\tau = \{LogNotional_\tau, LogTenor_\tau, LogCustomization_\tau, Volatility_\tau, Buy_\tau\},$$

where $LogNotional_\tau$ is the log notional amount of the transaction, $LogTenor_\tau$ is the log tenor (in days) of a forward contract, $LogCustomization_\tau$ is a measure of contract customization given by one plus the absolute difference (in logs) between the tenor of a forward contract and its nearest standard tenor, $Volatility_\tau$ is the 30-minute realized volatility of the FX spot rate (based on one-minute intervals), and *Buy* is a dummy that takes the value of one when a client commits to buy euros (in exchange for dollars) and zero otherwise.

3.5.1 Conditional Average Client Spreads

To assess the scope of discriminatory pricing in the OTC FX derivatives market, we first compare the unconditional distribution of the average spread to its conditional distribution. The conditional distribution is given by the distribution of client fixed effects μ_i in the linear regression:

$$Spread_{i,b,\tau} = \mu_i + Z_\tau\beta_2 + \delta_d + \gamma_t + \gamma_m + \epsilon_\tau,$$

which controls for the contract characteristics Z_τ of each trade τ, the identity of each dealer through the fixed effect δ_d, and additional fixed effects for the time-varying market conditions γ_t and γ_m. By contrast, the unconditional distribution of average spreads is obtained if we drop the control terms Z_τ, δ_d, γ_t, and γ_m from the regression.

Both the unconditional and conditional distributions of the average spread μ_i are depicted as histograms in Figure 3.4. The two distributions are strikingly similar. This implies that differences in average spreads across clients cannot be attributed to differences in contract characteristics, dealer efficiency or market timing. Instead, they are inherent to the client identity, which defines discriminatory pricing. Moreover, the degree of discriminatory pricing is economically large: the client at the 75th percentile pays an average spread of 30.1 pips—2.5 times that of the median client, which transacts at a spread of only 12.1 pips, and 12 times that of the client at the 25th percentile, which transacts at a competitive spread of 2.5 pips. In the next section, we explore the determinants of this large degree of discriminatory pricing.

3.5.2 Client Sophistication

To explore the relationship between discriminatory pricing and client characteristics, we use the following set of proxy variables for client sophistication:

$$X_i = \{Log\#Counterparties,\ HHI,\ LogTotalNotional,\ Log\#TradesFX,\ Log\#TradesNonFX\}.$$

Replacing the client fixed effects in the previous specification with these variables produces the regression estimates reported in Table 3.2. Columns (1) to (5) introduce each of the sophistication measures separately, while controlling for transaction characteristics and dealer, date, and minute-of-day fixed effects. Column (1) indicates that clients with more counterparties pay lower spreads on average, consistent with Hypothesis 1. Similarly, Column (2) indicates that clients with more concentrated counterparties pay higher spreads. In Columns (3) and (4), we find that more active clients, in terms of number of trades and the notional traded respectively, obtain lower spreads. Finally, Column (5) shows that clients with more outstanding derivatives contracts in other asset classes benefit from lower spreads on average. Column (6) synthesizes these results using a summary measure of sophistication based on the first principal component of the five individual sophistication measures. The estimated coefficient is -1.509 and statistically significant at the 1% level. This point estimate implies that a one standard deviation increase in client *Sophistication* is associated with an average spread reduction by 2.7 pips.

Overall, the results reported in Table 3.2 provide strong support for Hypothesis 1. All proxies of client sophistication have the expected sign, and are highly statistically significant. Not reported here are regression results for other proxies of client sophistication, such as their (log) asset size, which shows that smaller clients tend to pay higher spreads. Yet, most of our sophistication measures tend to be correlated with each other so that their marginal explanatory power decreases. A variance decomposition shows that client fixed effects account for 40% of the total spread variation across all trades. By comparison, the client sophistication proxies X_i together account for 8% of the total spread variation, which explains 20% of the discriminatory pricing embodied in the client fixed effects. Imperfect measurement of client sophistication implies that 20% represents a lower bound on the share of discriminatory pricing that can be attributed to variation in client sophistication.

A more intuitive way of illustrating the economic significance of client sophistication for price discrimination is provided in Figure 3.5, which plots the average spread of all clients with the same number of dealer counterparties against the number of counterparties ($\#Counterparties$). The size of the symbol represents the notional share for each group of clients. Clients with only one dealer counterparty account for 2% of the notional and 68% of the 10,062 clients engaged in risk hedging; these less sophisticated clients trade at an average spread of 17.5 pips. With each additional dealer counterparty, the average spread falls substantially, and reaches 5 pips when clients have four counterparties. For the groups of clients trading with five or more dealers, the average spread is around 2 pips or less, which can be considered a benchmark for the competitive spread. While this group represents only 6% of all clients, their aggregate notional accounts for 89% of the total.

3.5.3 Contract Characteristics

The regression results reported in Table 3.2 control for a variety of contractual features. The role of these features in determining spreads is also of interest. We find that contracts with a larger $LogNotional$ generally exhibit lower spreads. This finding is consistent with evidence from other OTC markets, notably the bond market (Schultz, 2001; Green et al., 2006). This trade size discount is robust to controlling for sophistication, which includes the effects of counterparty size (e.g., via $LogTotalNotional$). But given that dealer revenue scales linearly in the notional value of each trade (as the spread is computed per unit), a negative coefficient is likely to reflect a fixed cost component of the transaction cost of a trade.

Moreover, we find that longer contract maturity ($LogTenor$) is associated with larger spreads, perhaps because forwards of longer duration expose dealers to greater market risk. The coefficient of $Volatility$ has the expected positive sign, but is statistically insignificant. This low level of statistical significance is due to the inclusion of date and minute-of-day fixed effects, which absorb most of the variation in volatility. Further, the dummy variable for *Buy* trades is statistically significant. The observed aggregate demand imbalance between long and short positions in the European market segment can explain these more favorable spreads for buy than for sell trades.

Finally, we cannot reject Hypothesis 6. Trades with a tenor that differs from a standard maturity do indeed command a spread premium. However, the economic magnitude of this effect is relatively modest. An increase in the customizing measure by one standard deviation is associated with a spread increase of approximately 1 pip.

3.5.4 Multi-Dealer Request-for-Quote Platforms

As centralized exchange trading is often proposed as a remedy for monopolistic pricing practices in OTC markets, it is insightful to explore whether the use of multi-dealer RFQ platforms is associated with spread compression. As discussed previously, the ability to simultaneously query multiple dealers on RFQ platforms allows clients to put dealers into competition with each other for a particular trade, similar to a privately organized batch auction. In our one-year sample, 40.9% of the 556,297 EUR/USD forwards are executed via a multi-dealer RFQ platform. These trades are executed by just 1,219 clients (i.e. 12.2% of our full sample), which means that the vast majority of clients never use an RFQ platform to trade FX forwards.

According to Hypothesis 2, clients using RFQ platforms are expected to enjoy lower spreads. Figure 3.6 suggests that this is indeed the case. It plots the average spread for the 10,062 clients as a function of their sophistication. Lower client sophistication implies a much larger dispersion of the average spread. This is partly explained by larger sampling errors, as sophistication correlates negatively with the number of trades used for calculating average spreads. But the more important feature of the figure is the marked difference in the average transaction spread of RFQ platform trades (marked by red crosses) and non-platform trades (marked by blue dots) represented by a dashed and solid black line, respectively. While the average spreads are extremely low and mostly invariant to client sophistication for platform trades, bilateral trades feature a steep cost increase as client sophistication declines. Visually, price discrimination based on sophistication disappears almost entirely if a client uses an RFQ platform for its trade execution.

In Table 3.3, we investigate the effect of platform use on spreads by conditioning on contract characteristics, counterparty identities, and market conditions. Column

(1) indicates that trading through a platform is associated with an average spread reduction of 7.2 pips. However, this specification does not control for client sophistication, which represents an important conditioning variable for the benefits of platform use. By including the $Sophistication$ variable and its interaction with the $RFQPlatform$ dummy in Column (3), we can gauge how platform use improves execution quality for clients with different levels of sophistication. As sophisticated clients already obtain low spreads, the incremental spread compression should be largest for the least sophisticated, as predicted by Hypothesis 2.

The estimated coefficients reported in Column (3) confirm this intuition. The point estimate of -1.925 for $Sophistication$ indicates an economically strong negative relationship between spreads and sophistication. Yet, this relationship is completely eliminated for RFQ platform users, as indicated by the positive coefficient of 1.964 for the interaction term $RFQPlatform \times Sophistication$; adding the relevant coefficients together implies a zero net effect for sophistication. This conditional analysis implies that the discriminatory spread mark-up for less sophisticated clients vanishes on RFQ platforms. More broadly, it confirms the visual impression given by Figure 3.6: The lower the level of client sophistication, the greater the benefit of platform use in improving trade execution quality.

The economic magnitude of the spread compression on multi-dealer RFQ platforms may be surprising. Non-anonymity of counterparties is a necessary feature of such trading systems, because trades are not centrally cleared and thus carry counterparty credit risk. Discriminatory pricing based on client sophistication is therefore still feasible. Yet, the lack of client anonymity does not impair the considerable improvement in execution quality obtained through these platforms.

In unreported results, we find that the benefits of trading via RFQ platforms are present even if a client always executes its trades with the same dealer. To obtain this finding, we repeat the specifications estimated in Table 3.3 using only the subsample of clients which only ever trade with one dealer in our data sample. The coefficients of the $RFQPlatform$ variable are negative and significant even when estimated on this restricted sample. At first glance, this result might seem surprising, since dealers know the identity of the client when submitting a quote, and can therefore discriminate based on that client's sophistication. However, on RFQ platforms, dealers do not know the number of dealers from which a client simultaneously requests quotes. Hence, clients can benefit from this information asymmetry as platform-based requests for quotes signal outside trading options with other dealers even if these are either not available or not used in equilibrium.

3.5.5 Information Rents and Asymmetric Price Adjustment

OTC derivatives markets generally lack price transparency. Is this an important source of dealers' market power? Hypothesis 3 suggests that dealers derive profits from better access to real-time price data. We can test for the existence of such information rents around changes in the market mid-price. If clients are not aware of recent changes in the mid-price, they are more likely to accept outdated ("stale") transaction prices, thus generating information rents for the dealer. Importantly, dealers can only exploit recent price changes when they occur in the opposite direction of the client's trading intention. This gives rise to an asymmetric price adjustment.

In Table 3.4, Columns (1) reports the coefficient estimates of a regression of spreads on $|\Delta m_{\tau}^{-d}|$ and $|\Delta m_{\tau}^{+d}|$ as well as $Sophistication$ and the usual set of control variables, namely contract characteristics and dealer, date, and minute-of-day fixed effects. For robustness, columns (3) and (6) additionally report the estimates for mid-price changes in the last 60 and 90 second intervals prior to the transaction, respectively.

For the 30-second interval, the coefficient of $|\Delta m_{\tau}^{-d}|$ is 0.391 and statistically significant at the 1% level. This indicates that dealers do indeed charge higher spreads when a trade is preceded by a price change in the opposite direction from the client order, as compared to a static mid-price. However, the coefficient of $|\Delta m_{\tau}^{+d}|$ is negative and also statistically significant at -0.229; hence, clients enjoy lower spreads when their trade is preceded by a mid-price change in the same direction of the trade compared to a static mid-price. This implies that dealers update their price offers only in a sluggish manner, even if this squeezes their spreads. However, the sum of both coefficients is statistically different from zero for pre-trade intervals of 30 and 90 seconds. This is consistent with the existence of information rents earned through asymmetric price adjustment following changes in the mid-price.

As seen in subsection 3.5.4, trading on multi-dealer RFQ platforms helps clients to reduce dealers' market power and eliminate discriminatory pricing. Hypothesis 3 suggests that RFQ platforms should also reduce information rents. Accordingly, we expect the observed asymmetry in price adjustment to be particularly prevalent for bilateral trades, and absent for platform trades. To examine this, we add the $RFQPlatform$ dummy and its interactions with $|\Delta m_{\tau}^{-d}|$ and $|\Delta m_{\tau}^{+d}|$ to the regression specification. The results in Columns (2), (4) and (6) are consistent with the prediction. For off-platform trades, the asymmetry in price adjustment at the 30-second interval becomes larger with point estimates of 0.581 and -0.256 for $|\Delta m_{\tau}^{-d}|$ and $|\Delta m_{\tau}^{+d}|$, respectively. However, platform trades do not share in this asymmetric price adjustment. For example, the point estimates of -0.515 for the interaction term $|\Delta m_{\tau}^{-d}| \times RFQPlatform$ in Column (2) cancels the contribution of the baseline coefficient of 0.581 of $|\Delta m_{\tau}^{-d}|$. This indicates that RFQ platform trading greatly reduces the information rents earned by dealers.

To summarize, OTC market opacity is a source of market power for dealers. This finding is consistent with prior evidence of asymmetric price adjustments in the US municipal bond market (Green et al., 2010). Moreover, we show that these information rents vanish once dealers compete on RFQ platforms.

3.5.6 Client-Dealer Relationships

Hypothesis 4 predicts that the existence of client-dealer relationships lowers spreads. Different from the existing literature, we not only rely on observed trading relationships, but also make use of the existence of client-dealer ties in credit markets, thus alleviating possible endogeneity concerns.

Table 3.5, Columns (1) and (2) show the regression results for the first set of relationship variables based on the respective bilateral volume share of activity for the client i and the dealer d. In Column (1), we observe that clients pay higher spreads when trading with their relationship bank(s). An increase in a client's trading share with a dealer by 10 percentage points of its total notional increases its average spread by about 1 pip. Clients that are important to their dealers receive discounts of a similar magnitude.

In Column (2), we also control for client sophistication. Less sophisticated clients tend to have more concentrated trading relationships with particular dealers, but due to their smaller size matter less to their main dealer. After including client sophistication in the specification, the magnitude of both of the aforementioned coefficients diminishes substantially. However, we still observe that clients pay higher spreads by around 0.3 pips if their notional share with a particular dealer increases by 10 percentage points. In contrast, dealers seem not to discriminate across clients of different relative importance once we control for *Sophistication*.

Alternatively, we measure client-dealer relationships through the existence of bilateral ties in the credit market. The dummy variable *Relationship* marks all client-dealer trades for which there exists an additional credit relationship outside the derivatives market. We find that clients tend to pay higher spreads to their relationship dealers even after controlling for *Sophistication*. Overall, these findings are at odds with models in which relationships procure transactional benefits (Hendershott et al., 2017).

3.5.7 Client Credit Risk

The absence of central clearing or widespread collateralization in the FX derivatives market creates credit risk. Hypothesis 5 posits that client credit risk is compensated by higher spreads. To test this hypothesis, we augment the baseline regression with two alternative proxies for client credit risk, namely *ZScore* and *CashFlowVol*. The results are presented in Table 3.6, Columns (1) and (2), respectively. Columns (3) and (4) add *Sophistication* as an additional control variable.

The positive and statistically significant coefficient of *ZScore* in Column (1) suggests that low-risk clients (with a high *ZScore*) pay higher spreads. This is at odds with Hypothesis 5, which predicts that dealers charge higher spreads to riskier clients in compensation for credit risk. *CashFlowVol*, the second measure of client risk in Column (2), is not associated with higher spreads. After controlling for client *Sophistication* in Columns (3) and (4), neither of the coefficients for the two risk measures is statistically significant.

While our finding that credit risk is not priced may be surprising, it is broadly consistent with existing evidence. Arora et al. (2012) and Du et al. (2016) examine the role of counterparty risk in the CDS market. While they find the effect of credit risk on prices to be statistically significant, the economic magnitude is extremely small.

3.6 Conclusion

New regulatory derivatives data with counterparty identities allow for the first time a comprehensive analysis of spreads for non-financial clients in the highly liquid segment of EUR/USD FX forwards. We highlight four findings:

First, clients trade at very heterogeneous spreads, even after controlling for contract characteristics, dealer fixed effects, and market conditions. We find that the client at the 75th percentile of the conditional spread distribution pays 30 pips on average over the market mid-price. This compares to competitive spreads of less than 2.5 pips paid by clients in the bottom 25% of the distribution.

Second, various proxies of client sophistication are strongly correlated with the degree of discriminatory pricing a client experiences. These proxies include a client's number of dealers, concentration of trading across dealers, the aggregate notional traded, and the total number of trades in FX and non-FX derivatives. Extensive discriminatory pricing in the OTC market occurs largely at the expense of unsophisticated clients.

Third, we document that the use of multi-dealer RFQ platforms removes the market power of dealers and compresses average spreads to a competitive level. The largest benefits accrue to the least sophisticated clients, because RFQ platform trading fully eliminates discriminatory pricing based on client sophistication. This occurs despite of the fact that dealers know the identity of their clients in RFQ platforms, unlike in an anonymous limit order book.

Fourth, we document that dealers benefit from opacity in the OTC market by exploiting recent prices movement to their advantage. In particular, changes in the mid-price are shown to trigger an asymmetric price adjustment whereby dealers do not pass on changes in the mid-price that would otherwise be to the benefit of the client. However, RFQ platform trades do not exhibit such a pattern, suggesting that they curtail information rents.

Overall, these results suggest that the current OTC market structure for FX derivatives can be improved. Multi-dealer platforms appear effective at reducing dealers' market power and the associated price discrimination against less sophisticated clients. However, more than half of clients' trades (conducted by almost 90% of clients) continue to be conducted bilaterally. Accordingly, mandating trading on organized platforms would benefit less sophisticated clients and possibly induce additional firms with latent exchange rate exposure to participate in the market. From this perspective, the fact that FX derivatives have eluded regulatory requirements—notably under the US Dodd-Frank Act and the EU's MiFID II—to be traded on organized platforms is puzzling.

Panel A: Client Data	Obs.	Mean	St.Dev	p10	p25	p50	p75	p90
$AvClientSpread$	10062	18.1	26.6	-3	2.0	14.3	33.9	52.6
$\#Counterparties$	10062	1.8	2	1	1	1	2	3
HHI	10062	0.8	0.3	0.1	0.6	1	1	1
$TotalNotional$ (in Euro mn)	10062	539.1	7480.2	0.1	0.4	1.8	11.2	116.1
$\#TradesFX$	10062	55.3	411.4	1	3	8	24	85
$\#TradesNonFX$	10062	14.7	232.7	0	0	0	0	3
$Sophistication$	10062	0	1.8	-1.7	-1.2	-0.5	0.7	2.4
$Notional_{i,d}/Notional_i$	10062	0.9	0.2	0.5	0.9	1	1	1
$Notional_{i,d}/Notional_d$	10062	0.01	0.08	0.000001	0.000005	0.00005	0.0008	0.010
$Relationship$	6621	0.6	0.5	0	0	1	1	1
$ZScore$	6173	2.9	1.8	1.0	1.8	2.7	3.8	5.1
$CashFlowVol$	6793	0	1	-0.3	-0.2	-0.1	0.1	0.6

Panel B: Transaction Data	Obs.	Mean	St.Dev	p10	p25	p50	p75	p90
$Spread$	556297	6.6	19.2	-4.9	-1.2	1.9	10.7	30.4
$Notional$ (in Euro mn)	556297	9.8	53.1	0.02	0.06	0.3	1.9	15
$Tenor$	556297	68.5	80.2	2	9	35	96	188
$Customization$	556297	10.6	16.7	1	2	3	12	33
$Volatility$	556297	0.007	0.004	0.004	0.005	0.006	0.008	0.01
Buy	556297	0.4	0.5	0	0	0	1	1
$RFQPlatform$	556297	0.4	0.5	0	0	0	1	1
$\lvert\Delta m_\tau^{-d}\rvert$	554357	0.5	1	0	0	0	1	1.5
$\lvert\Delta m_\tau^{+d}\rvert$	554357	0.5	0.9	0	0	0	1	1.5

Note: Panel A shows client-level data for the 10,062 non-financial clients that trade at least one EUR/USD forward with a dealer between April 2016 and March 2017, and Panel B shows transaction-level data for 556,297 EUR/USD forward trades. In Panel A, *Av.ClientSpread* is the average spread that a client pays on its trades with dealers. *#Counterparties* is the number of dealers with which a client trades. HHI is the Herfindahl-Hirschman index of the degree of concentration of a client's counterparty relationships with dealers. *TotalNotional* (in Euro mn) is the total notional traded by a client during the sample period. *#TradesFX* is the number of forwards traded by a client. *#TradesNonFX* is the total number of a client's outstanding interest rate, credit and commodity derivatives positions at the beginning of our sample period. *Sophistication* is the first principal component of *Log#Counterparties*, HHI, *LogTotalNotional*, *Log#TradesFX*, and *Log#TradesNonFX*. $Notional_{i,d}/Notional_i$ and $Notional_{i,d}/Notional_d$ quantify the notional traded in EUR/USD forwards between a client and dealer relative to the total EUR/USD notional traded by a client and dealer, respectively. *Relationship* is the share of forwards that a client trades with its relationship bank(s). *ZScore* is a client's modified Altman Z-score, calculated as the linear combination of working capital, retained earnings, profits, and sales. *CashFlowVol* is a client's standardized coefficient of variation of cash flows. In Panel B, *Spread* is the difference (in pips) between the contractual forward rate and the mid-price. *Notional* (in Euro mn) is the notional of each forward contract. *Tenor* is a trade's original maturity (in days). *Customization* is the difference in days between the tenor of a forward contract and its nearest standard tenor (i.e. 0, 1, 7, 30, 60, 90, 180, 270, or 360 days). *Volatility* is defined as the realized volatility of the FX spot rate over the preceding 30 minutes, based on one minute intervals. *Buy* is a dummy which equals one when a client forward-buys euro against dollar, and 0 otherwise. *RFQPlatform* is a dummy equal to one when a trade is executed via a multi-dealer electronic trading platform, and zero otherwise. $\lvert\Delta m_\tau^{-d}\rvert$ ($\lvert\Delta m_\tau^{+d}\rvert$) is the absolute value of the change in the mid-price over the preceding 30 seconds (in pips) if the price change was in the opposite (same) direction of the client order, and zero otherwise.

Table 3.1: *Summary Statistics*

	(1)	(2)	(3)	(4)	(5)	(6)
Sophistication measures:						
Log#Counterparties	-3.887***					
	(0.216)					
HHI		8.997***				
		(0.710)				
LogTotalNotional			-1.541***			
			(0.069)			
Log#TradesFX				-1.777***		
				(0.098)		
Log#TradesNonFX					-0.994***	
					(0.101)	
Sophistication						-1.509***
						(0.073)
Transaction controls:						
LogNotional	-0.602***	-0.462***	-0.293***	-1.079***	-0.785***	-0.588***
	(0.078)	(0.103)	(0.088)	(0.096)	(0.100)	(0.081)
LogTenor	1.118***	1.158***	0.916***	1.082***	1.180***	1.056***
	(0.092)	(0.094)	(0.088)	(0.090)	(0.094)	(0.090)
LogCustomization	0.941***	1.127***	0.868***	0.872***	1.007***	0.925***
	(0.102)	(0.122)	(0.100)	(0.103)	(0.115)	(0.103)
Volatility	6.465	5.536	2.965	3.634	9.661	4.221
	(15.833)	(15.717)	(15.956)	(15.572)	(15.703)	(15.710)
Buy	-6.449***	-6.678***	-6.164***	-6.368***	-6.600***	-6.341***
	(0.302)	(0.311)	(0.293)	(0.301)	(0.332)	(0.297)
R-squared	0.276	0.270	0.288	0.273	0.259	0.282
Obs.	556297	556297	556297	556297	556297	556297
Dealer FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Minute of day FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports OLS regressions of the transaction spread on measures of client sophistication. The sophistication measures and transaction controls are defined in the footnote to Table 3.1. One, two and three asterisks represent statistical significance at 10%, 5% and 1% respectively. Standard errors clustered at client level are reported in parentheses.

Table 3.2: *Client Sophistication (Hypothesis 1)*

	(1)	(2)	(3)
RFQPlatform	-7.219***	-3.766***	-13.25***
	(0.459)	(0.427)	(0.604)
Sophistication		-1.189***	-1.925***
		(0.084)	(0.079)
RFQPlatform $\times$ *Sophistication*			1.964***
			(0.124)
R-squared	0.269	0.287	0.299
Obs.	556297	556297	556297
Dealer FE	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
Minute of day FE	Yes	Yes	Yes
Transaction controls	Yes	Yes	Yes

Note: This table reports OLS regression estimations of transaction spreads on *RFQPlatform*, which is a dummy equal to one when a transaction was executed via a request-for-quote multi-dealer electronic trading platform, and zero otherwise. In addition, in Column (3), we interact *RFQPlatform* with *Sophistication*. The latter variable is the first principal component of *Log#Counterparties*, *HHI*, *LogTotalNotional*, *Log#TradesFX*, and *Log#TradesNonFX*. In addition, each specification controls for transaction characteristics (i.e. *LogNotional*, *LogTenor*, *LogCustomization*, *Volatility*, and *Buy*). One, two and three asterisks represent statistical significance at 10%, 5% and 1% respectively. Standard errors clustered at client level are reported in parentheses.

Table 3.3: *Request-for-Quote Multi-Dealer Platform Trades (Hypothesis 2)*

	Mid-price move in the preceding:					
	30 Seconds		60 Seconds		90 Seconds	
	(1)	(2)	(3)	(4)	(5)	(6)
$\lvert\Delta m_\tau^{-d}\rvert$	0.391***	0.581***	0.334***	0.497***	0.333***	0.481***
	(0.054)	(0.063)	(0.037)	(0.047)	(0.034)	(0.042)
$\lvert\Delta m_\tau^{+d}\rvert$	-0.229***	-0.256***	-0.293***	-0.364***	-0.232***	-0.285***
	(0.051)	(0.072)	(0.037)	(0.054)	(0.033)	(0.047)
$RFQPlatform$		-3.543***		-3.570***		-3.521***
		(0.432)		(0.431)		(0.433)
$\lvert\Delta m_\tau^{-d}\rvert \times RFQPlatform$		-0.515***		-0.448***		-0.413***
		(0.069)		(0.051)		(0.046)
$\lvert\Delta m_\tau^{+d}\rvert \times RFQPlatform$		0.0661		0.173***		0.129**
		(0.080)		(0.058)		(0.051)
$Sophistication$	-1.509***	-1.189***	-1.509***	-1.190***	-1.509***	-1.190***
	(0.074)	(0.084)	(0.074)	(0.084)	(0.074)	(0.085)
R-squared	0.283	0.289	0.284	0.289	0.284	0.290
Obs.	554356	554356	554356	554356	554356	554356
Dealer FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Minute of day FE	Yes	Yes	Yes	Yes	Yes	Yes
Transaction controls	Yes	Yes	Yes	Yes	Yes	Yes
P-value 1	0.0646	0.0024	0.5013	0.1037	0.0563	0.0048
P-value 2		0.0001		0.0014		0.0001
P-value 3		0.0362		0.0644		0.0046
P-value 4		0.0002		0.0000		0.0000
P-value 5		0.0775		0.0000		0.0004

Note: This table reports OLS regression estimations of transaction spreads on measures of price staleness. $|\Delta m_\tau^{-d}|$ ($|\Delta m_\tau^{+d}|$) is the absolute value of the change in the mid-price over the preceding 30, 60 or 90 seconds (in pips) if the price change was in the opposite (same) direction of the client order, and zero otherwise. In Columns (2), (4) and (6), these variables are interacted with *RFQPlatform*, which is a dummy equal to one when a transaction was executed via a multi-dealer electronic trading platform, and zero otherwise. *Sophistication* is the first principal component of *Log#Counterparties*, *HHI*, *LogTotalNotional*, *Log#TradesFX*, and *Log#TradesNonFX*. In addition, each specification controls for transaction characteristics (i.e. *LogNotional*, *LogTenor*, *LogCustomization*, *Volatility*, and *Buy*). P-values 1-5 refer to the following hypothesis tests. P-value 1: $|\Delta m_\tau^{-d}|=-|\Delta m_\tau^{+d}|$. P-value 2: $|\Delta m_\tau^{-d}| \times RFQPlatform=-|\Delta m_\tau^{+d}| \times RFQPlatform$. P-value 3: $|\Delta m_\tau^{+d}| + |\Delta m_\tau^{+d}| \times RFQPlatform = 0$. P-value 4: $|\Delta m_\tau^{-d}| + |\Delta m_\tau^{-d}| \times RFQPlatform = 0$. P-value 5: $|\Delta m_\tau^{-d}| + |\Delta m_\tau^{-d}| \times RFQPlatform=-|\Delta m_\tau^{+d}| - |\Delta m_\tau^{+d}| \times RFQPlatform$. One, two and three asterisks represent statistical significance at 10%, 5% and 1% respectively. Standard errors clustered at client level are reported in parentheses.

Table 3.4: *Asymmetric Price Adjustment (Hypothesis 3)*

	(1)	(2)	(3)	(4)
$Notional_{i,d}/Notional_i$	9.899***	3.038***		
	(0.630)	(0.876)		
$Notional_{i,d}/Notional_d$	-10.11***	0.206		
	(3.103)	(3.052)		
Relationship			3.568***	1.274**
			(0.736)	(0.650)
Sophistication		-1.191***		-1.459***
		(0.115)		(0.083)
R-squared	0.274	0.283	0.249	0.282
Obs.	556297	556297	556297	556297
Dealer FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Minute of day FE	Yes	Yes	Yes	Yes
Transaction controls	Yes	Yes	Yes	Yes

Note: This table reports OLS regression estimations of transaction spreads on measures of client-dealer relationships. First, $Notional_{i,d}/Notional_i$ and $Notional_{i,d}/Notional_d$ quantify the notional traded in EUR/USD forwards between a client and dealer relative to the total EUR/USD notional traded by a client and dealer respectively. Second, *Relationship* is a transaction-level dummy that takes the value of one when a client trades a forward with its relationship bank(s), and zero otherwise. In Columns (3) and (4), we replace missing observations on *Relationship* with an arbitrary constant value; to account for this, we include in the regressions a dummy which equals one when the observation on *Relationship* was originally missing, and zero otherwise. In Columns (2) and (4), we also include *Sophistication*, which is the first principal component of *Log#Counterparties*, *HHI*, *LogTotalNotional*, *Log#TradesFX*, and *Log#TradesNonFX*. In addition, each specification controls for transaction characteristics (i.e. *LogNotional*, *LogTenor*, *LogCustomization*, *Volatility*, and *Buy*). One, two and three asterisks represent statistical significance at 10%, 5% and 1% respectively. Standard errors clustered at client level are reported in parentheses.

Table 3.5: *Client-Dealer Relationships (Hypothesis 4)*

	(1)	(2)	(3)	(4)
ZScore	0.534***		-0.00359	
	(0.159)		(0.137)	
CashFlowVol		0.0839		-0.233
		(0.247)		(0.211)
Sophistication			-1.515***	-1.510***
			(0.073)	(0.074)
R-squared	0.245	0.244	0.282	0.282
Obs.	556297	556297	556297	556297
Dealer FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Minute of day FE	Yes	Yes	Yes	Yes
Transaction controls	Yes	Yes	Yes	Yes

Note: This table reports OLS regression estimations of transaction spreads on measures of client risk. *ZScore* is a client's modified Altman Z-score, calculated as the linear combination of working capital, retained earnings, profits, and sales. *CashFlowVol* is a client's standardized coefficient of variation of cash flows. We replace missing observations on *ZScore* and *CashFlowVol* with an arbitrary constant value; to account for this, we include in the regressions a dummy which equals one when the observation on *ZScore* and *CashFlowVol* was originally missing, and zero otherwise. In Columns (3) and (4), we also include *Sophistication*, which is the first principal component of *Log#Counterparties*, *HHI*, *LogTotalNotional*, *Log#TradesFX*, and *Log#TradesNonFX*. In addition, each specification controls for transaction characteristics (i.e. *LogNotional*, *LogTenor*, *LogCustomization*, *Volatility*, and *Buy*). One, two and three asterisks represent statistical significance at 10%, 5% and 1% respectively. Standard errors clustered at client level are reported in parentheses.

Table 3.6: *Client Credit Risk (Hypothesis 5)*

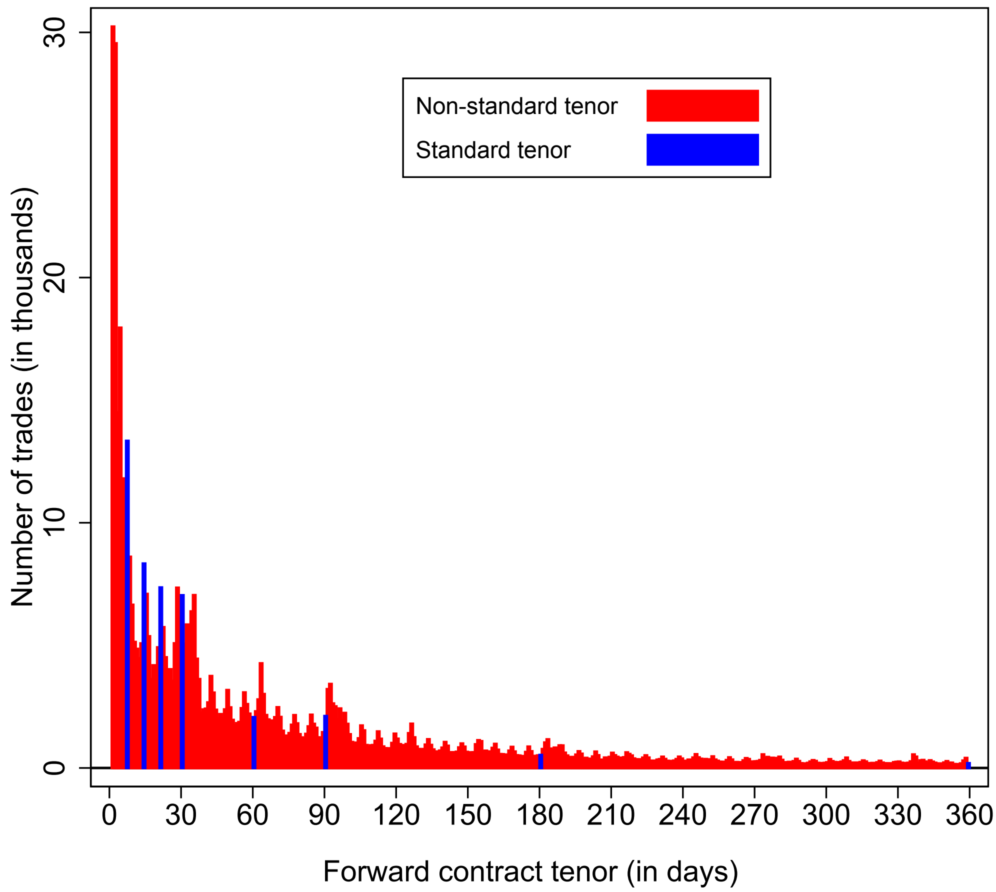

Figure 3.1: *Trade Distribution by Maturity Date*

Note: This figure plots the distribution of contract tenors (in days) for all 556,297 EUR/USD forwards traded between dealers and clients over April 1, 2016 to March 31, 2017. Blue bars denote trades at standard tenors, i.e. 7, 14, 21, 30, 60, 90, 180, and 360 days, and red bars denote trades at non-standard tenors.

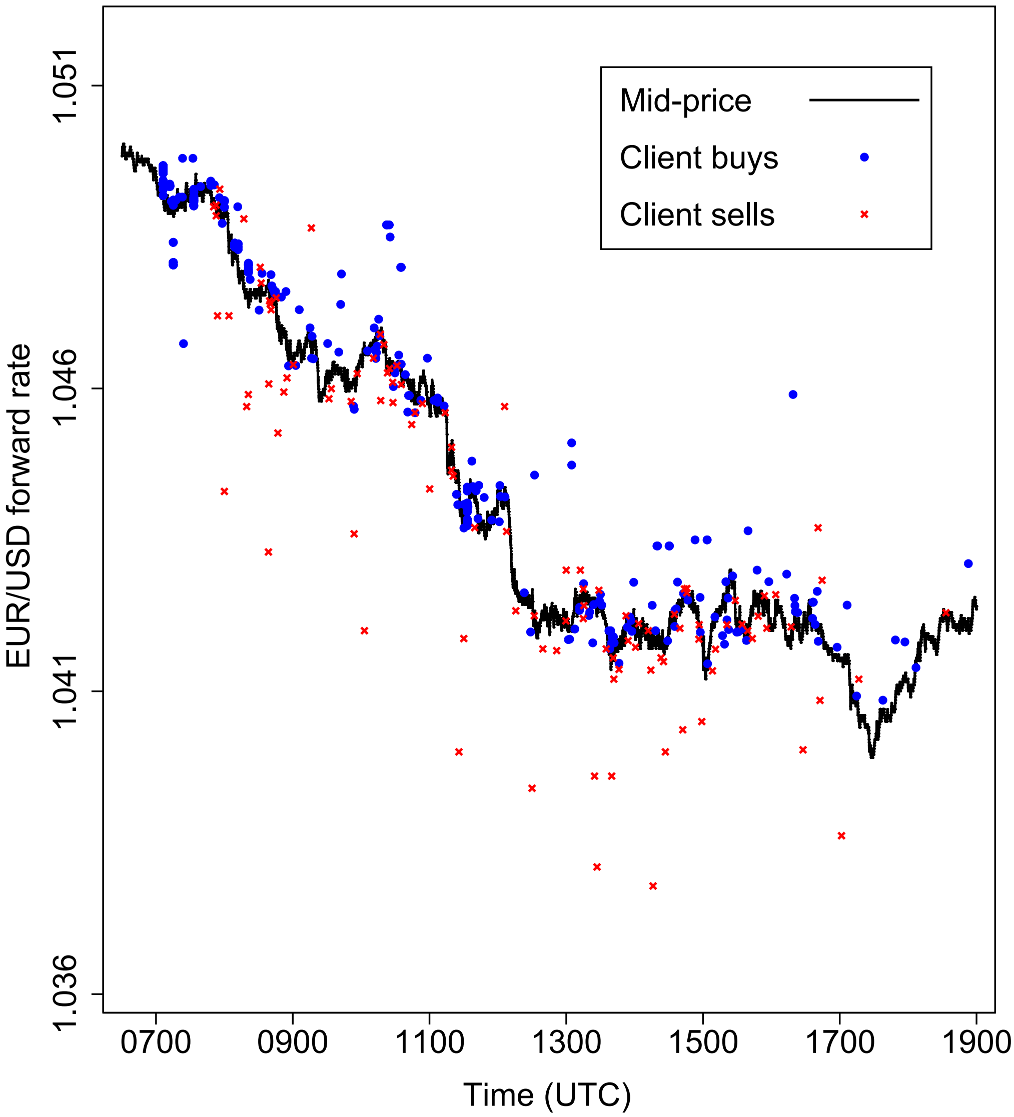

Figure 3.2: *Contracted Forward Rates versus the Mid-Market Rate*

Note: This figure plots contractual forward rates versus the mid-price on a given day (28 December 2016). The mid-price is shown by the solid black line, which tracks intraday mid-prices for one month EUR/USD forwards (as constructed from Thomson Reuters quote data). The contractual forward rates are shown by blue dots (for forwards in which the client buys euro against dollar) and red crosses (for forwards in which the client sells euro against dollar). For the latter, we only include forwards with an original maturity of between 25 and 35 days (to match the one month tenor of the mid-price). Blue dots (red crosses) above (below) the solid black line imply positive spreads for the client.

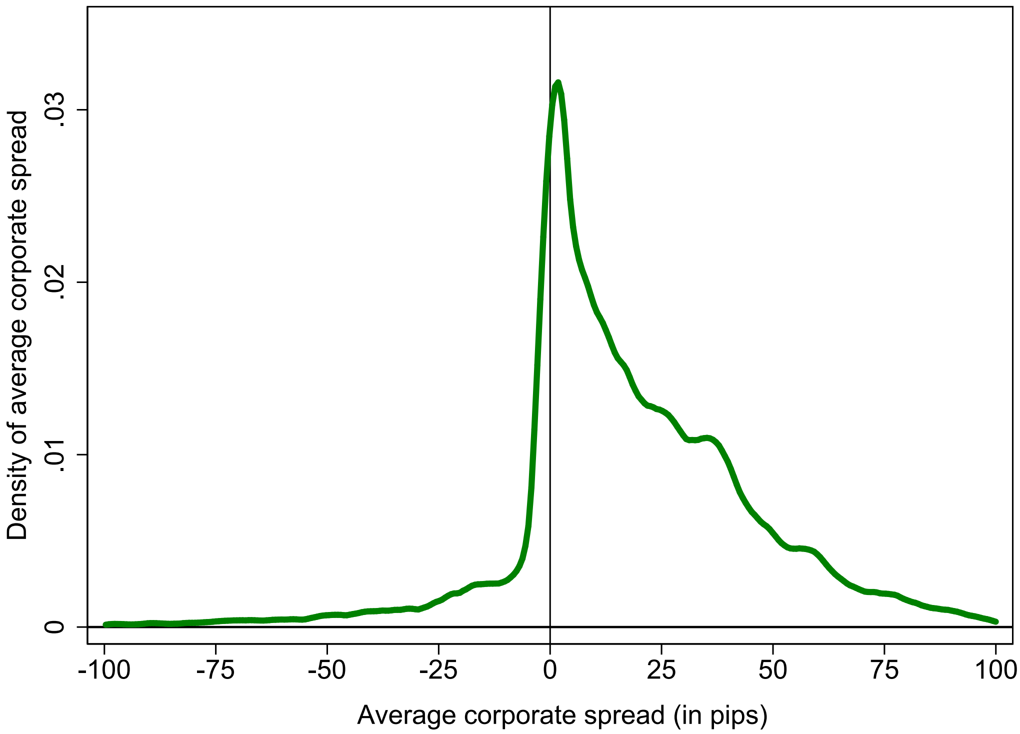

Figure 3.3: *Distribution of Average Client Spread*

Note: This figure plots the distribution of average spreads paid by the 10,062 clients that engage in 556,297 forward transactions with 204 dealers between April 1, 2016, and March 31, 2017. Positive spreads are costly to the client and advantageous to the dealer, and vice versa for negative spreads.

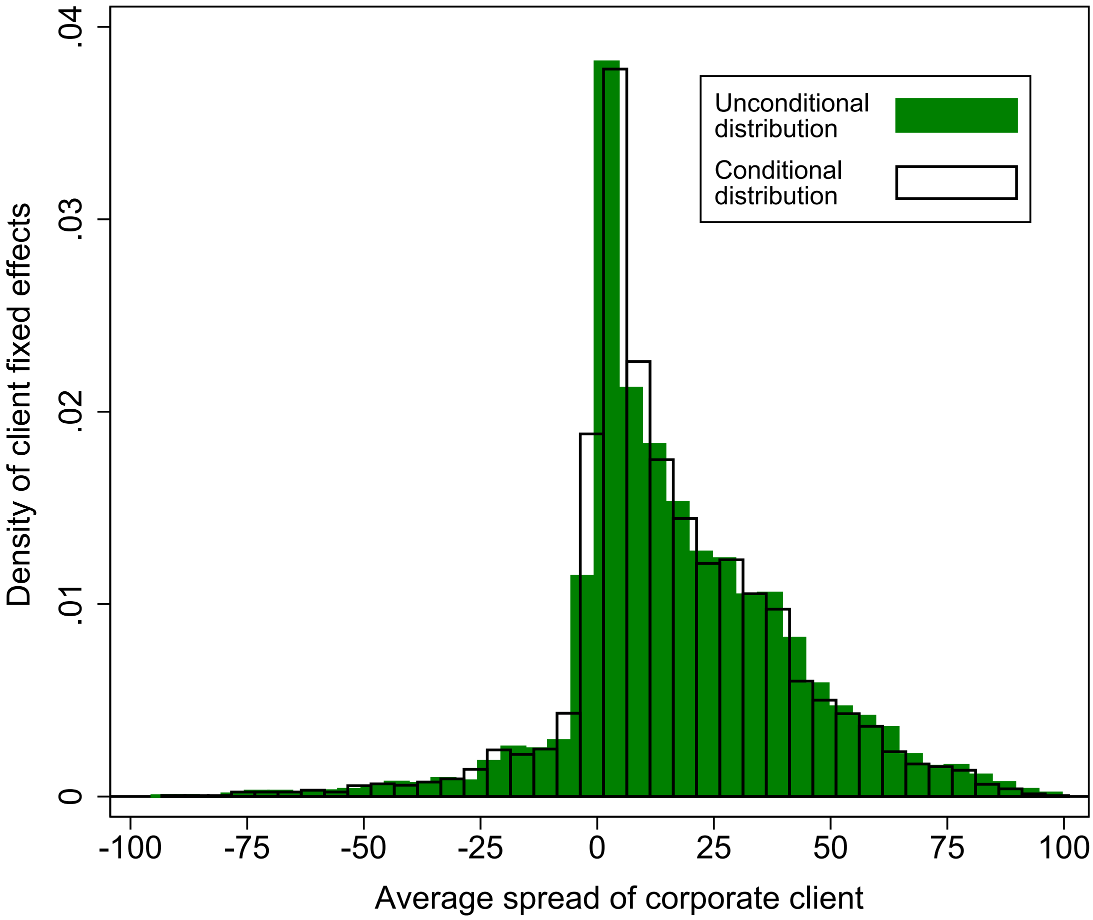

Figure 3.4: *Distributions of Conditional and Unconditional Average Client Spreads*

Note: This figure plots the distributions of conditional and unconditional average client spreads (in pips) for the 8,533 clients that traded more than one EUR/USD forward over April 1, 2016, to March 31, 2017. The unconditional distribution of average client spreads is calculated as in Figure 3.3. The distribution of conditional average client spreads controls for contract characteristics, dealer fixed effects, and market conditions.

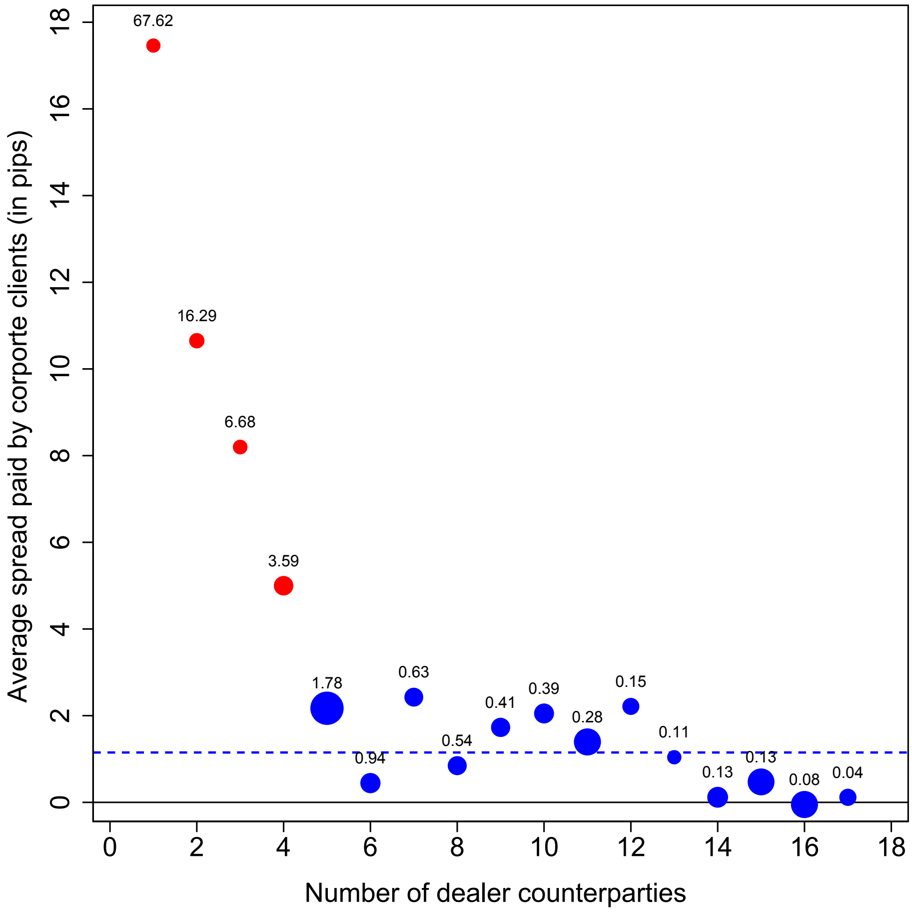

Figure 3.5: *Average Client Spread by Number of Dealer Counterparties*

Note: This figure plots the average spread paid by clients with a given number of dealer counterparties in the EUR/USD forwards market. Marker size represents the aggregate notional traded (in logs). Marker labels indicate the percentage of the 10,062 clients with a given number of dealer counterparties. Client groups with five or more dealer counterparties are colored blue; groups with four or fewer counterparties are colored red. The horizontal line plots the average spread paid by the client groups colored blue (i.e. 1.2 pips).

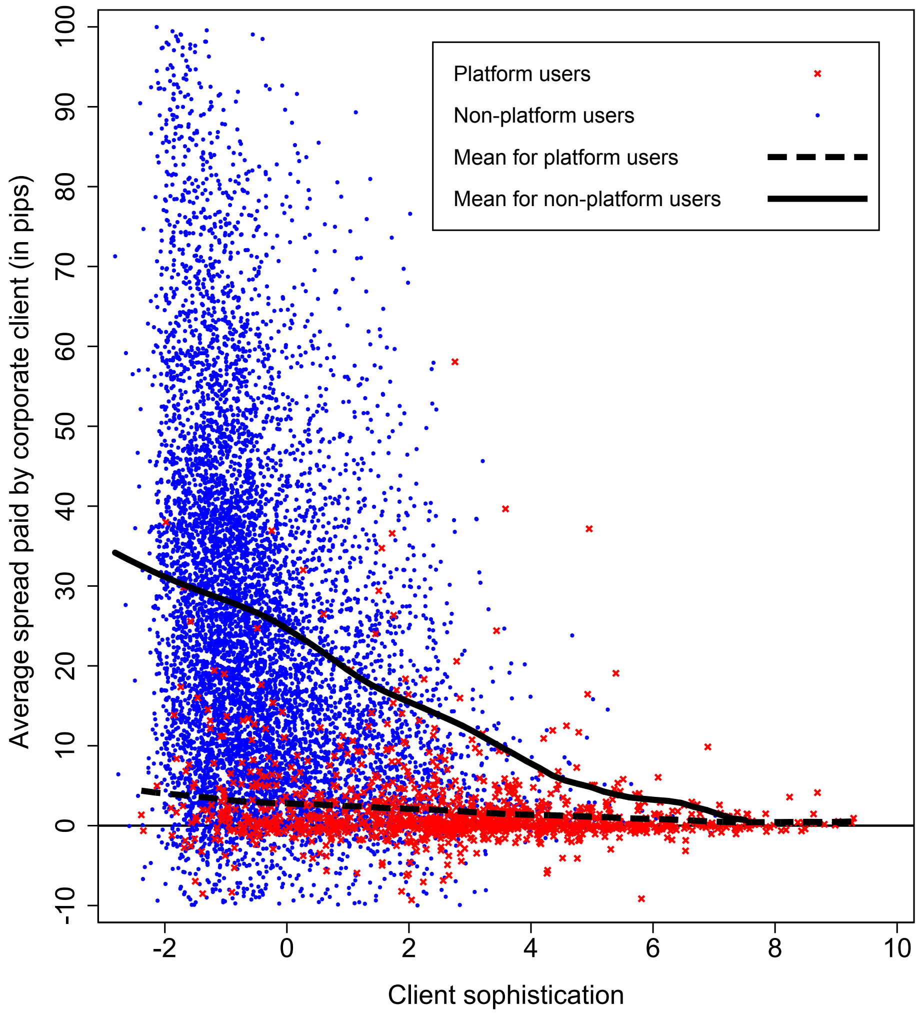

Figure 3.6: *Average Client Spread by Sophistication and Trade Execution Type*

Note: This figure plots the average spread paid by each client (on the vertical axis) against *Sophistication* (on the horizontal axis). *Sophistication* is the first principal component of *Log#Counterparties*, *HHI*, *LogTotalNotional*, *Log#TradesFX*, and *Log#TradesNonFX*. The solid black line plots the estimated Kernel-weighted local polynomial regression of average client spreads on *Sophistication*. The dashed black line plots the estimated Kernel-weighted local polynomial regression for the hypothetical case in which clients trade exclusively through request-for-quote multi-dealer electronic platforms, based on the estimates reported in Table 3.3, Column (3). For readability, the vertical axis is truncated at -10 pips.

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Chapter 4

Financial Frictions and the Great Productivity Slowdown[1]

[1]Co-authored with Romain Duval and Gee Hee Hong.

4.1 Introduction

Productivity growth has declined in advanced economies since the global financial crisis (GFC) and has remained weak ever since (Adler et al., 2017; OECD, 2015). Much attention in academic research has focused on whether the productivity slowdown reflects slowing innovation and technological diffusion (Andrews et al., 2015; Cette et al., 2016; Fernald, 2015; Gordon, 2016), amid declining business dynamism (Decker et al., 2016a,b). Yet the abruptness, magnitude and persistence of the fall in total factor productivity (TFP) growth after the GFC makes it difficult to blame the productivity slowdown solely on such slow-moving structural forces. A defining feature of the GFC was the sharp unanticipated tightening of credit supply conditions that took place in the aftermath of the collapse of Lehman Brothers on September 15th 2008. This paper argues that the interplay between tighter credit conditions and weak corporate balance sheets generated "TFP hysteresis," playing an important role in the puzzling post-crisis productivity slowdown in advanced economies.

Our empirical strategy exploits the sharp and unforeseen tightening of credit conditions that took place in the immediate aftermath of the collapse of Lehman Brothers on September 15th 2008. Using an extensive cross-country firm-level dataset put together by merging different waves of ORBIS, we start by showing that the decline in average within-firm TFP growth between the pre- and post-crisis periods was significantly larger for firms with greater pre-existing balance sheet vulnerabilities. This holds within narrowly defined country-industry cells − that is, controlling for any country-industry (supply or demand) shocks, and then comparing firms with strong vs. weak balance sheet vulnerabilities within each cell. We then show that pre-crisis balance sheet weakness was associated with a larger TFP slowdown for firms that faced a more severe tightening of credit conditions around Lehman − an exogenous event we measure either at the country level by the increase in the average CDS spread of domestic banks around September 15th 2008, or at the firm level by the increase in the average CDS spread of their main creditor banks. This further indicates that productivity was adversely affected by an interaction between a credit supply shock and pre-existing corporate financial vulnerabilities. These estimated effects are highly persistent: the TFP level gap between more and less vulnerable firms opens up in 2009 and further increases in subsequent years, ruling out that we are capturing a cyclical phenomenon. These effects are also large; a simple back-of-the-envelope calculation suggests they may account for around a third of the within-firm TFP growth slowdown across our cross-country firm-level dataset between the six years before and six years after the crisis.

Our main measure of financial vulnerability captures ex-ante rollover-risk and is the amount of debt prior to the crisis that was scheduled to mature during the crisis, measured as the burden of current liabilities (maturing within a year) at the end of 2007. This "maturing-debt" empirical strategy is comparable to those followed in several recent papers (Almeida et al., 2011; Benmelech et al., 2011, 2017). Because the GFC was unforeseen, firms' debt structure prior to the crisis is unlikely to be correlated with other unobserved firm characteristics that might correlate with the magnitude of the decline in their TFP growth post-crisis. For this reason, debt maturing during the crisis is our preferred firm-level measure of financial vulnerability.

The causal interpretation of our estimates rests on two further grounds. First, the results are not driven by more vulnerable firms being less productive or having enjoyed slower productivity gains before the crisis − more and less vulnerable firms do not differ significantly along these or other relevant dimensions. Second, in a placebo test, we confirm that the change in within-firm TFP growth between the pre- and post-2000 recession periods was unrelated to pre-2000 balance sheet vulnerabilities. This underlines the peculiar nature of the GFC, which was associated with a massive credit supply shock, unlike the 2000 recession that followed the burst of the dot-com bubble.

Having established that financial frictions mattered for the post-GFC TFP slowdown, we then turn to the question of why they did so. While we do not provide a comprehensive answer to this question, we explore the role of weaker intangible investment as one among several possible channels. When credit markets froze after September 15th 2008, maturing debt could not be rolled over, or only at a much higher cost. The larger was the amount of maturing debt that could not be rolled over, the greater was the pressure on firms to reduce expenditure. Unlike intangible investment such as R&D or workforce training, most forms of physical capital can be pledged as collateral to obtain a loan, and they can translate more quickly into sales. Firms that had to roll over larger amounts of maturing debt had therefore a greater incentive to cut back on intangible investment, which in turn could have affected TFP. We find supportive evidence for this conjecture. Using the same empirical strategy as for our productivity analysis, we show that firms with pre-existing balance sheet vulnerabilities cut back on intangible investment more than their less vulnerable counterparts after the crisis, and that this divergence was larger in countries where credit conditions tightened more during Lehman. Other, unexplored but related factors may also have played a role, such as the sudden inability of high-rollover-risk firms to finance their working capital and thereby to use their inputs efficiently. However, the persistence of the firm-level TFP losses even as credit conditions gradually improved after Lehman suggests to us that temporarily weaker intangible asset investment, which permanently reduced the intangible capital stock, played a significant role.

Our paper relates to the recent literature on the effects of financial frictions on productivity. The dominant strand of this literature focuses on resource misallocation across firms (Hsieh and Klenow, 2009; Restuccia and Rogerson, 2008).[2] Some studies highlight that financial frictions can increase misallocation, and thereby weaken TFP, by preventing an optimal allocation of resources toward, and the entry of, more credit-constrained firms (Midrigan and Xu, 2014; Moll, 2014). Other papers highlight instead that credit booms due to large capital inflows, and lax credit conditions more broadly, can lead to misallocation of resources and productivity losses (Benigno et al., 2015; Borio et al., 2016; Gopinath et al., 2017). Our paper does not directly relate to this literature, as our focus is not on misallocation of resources between firms but instead on the much-less researched impact of financial frictions for within-firm productivity growth.[3]

More closely related to our work are papers by Aghion et al. (2010, 2012). Aghion et al. (2010) show theoretically that credit constraints can lead firms to cut R&D spending − and long-term illiquid investments more broadly − during recessions. Aghion et al. (2012) find supportive empirical evidence using French firm-level data. Compared with these papers, our work is novel in that we focus on productivity rather than only on R&D investment, highlight the role of specific firm-level vulnerabilities, and study their role for a broad cross-country firm-level dataset by exploiting the September 2008 collapse of Lehman Brothers as an exogenous

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[2]See Restuccia and Rogerson (2013) for a literature review on misallocation and productivity.

[3]Although we do not explicitly study this issue, our results still highlight one potential source of misallocation of resources between firms, namely the heterogeneous impact of credit conditions on within-firm TFP growth. This leads to greater dispersion in TFP between firms which, in the presence of frictions in capital and/or labor markets, should also increase dispersion in their marginal products of capital and/or labor. In that regard, our paper also bears some connection to the literature on the cleansing effect of recessions, which has highlighted that credit frictions could undo at least some of the positive cleansing effect of recessions emphasized in Caballero and Hammour (1998) by forcing the exit of productive but constrained firms (see for example Osotimehin and Pappadà (2017)).

credit supply shock. Theoretical models by Garcia-Macia (2015) and Anzoategui et al. (2016) further highlight that reduced investments in intangible assets can slow within-firm productivity growth. Our empirical evidence is consistent with this prediction.

Finally, our paper also relates to a recent literature on how the GFC affected firms. Giroud and Mueller (2017) find that U.S firms that had weaker balance sheets reduced employment more than their healthier counterparts. Chodorow-Reich (2013) show that banking frictions − having a relationship with a weak bank − also mattered, and Siemer (2014) finds that small young firms were most affected. Also focusing on the U.S, Benmelech et al. (2011) carry out several empirical exercises that highlight the broader role of financial frictions − including refinancing risk − for firms' labor force adjustment. Benmelech et al. (2017) estimate that such financial frictions contributed to sizeable job losses in large U.S firms during the Great Depression. All these studies focus on employment. Ridder (2016) also exploits variation in firm exposure to the GFC to study the real impact of credit constraints on U.S firms, but he does not focus on TFP. Closer to our paper, Huber (2018) exploits variation in German counties' and firms' exposure to a large bank's lending cut during the GFC, and finds that more exposed German counties and firms experienced larger and persistent declines in output, capital, employment and innovative activity (patenting). Our paper provides cross-country firm-level evidence of TFP hysteresis effects from financial frictions, and highlights their contribution to the permanent productivity and output losses from the GFC in advanced economies. We also identify one channel − lower intangible asset investment − through which such adverse "TFP hysteresis" effects may have arisen.

4.2 Empirical Strategy

4.2.1 Identification Approach

Our empirical setup is a differences-in-differences strategy that compares the difference in TFP growth between firms with high versus small pre-existing balance sheet vulnerabilities, after versus before the sharp unforeseen credit conditions tightening in 2008 after the collapse of Lehman Brothers. It bears similarities with Giroud and Mueller (2017), who study the impact of this credit supply shock on employment in U.S firms by regressing the change in firm-level employment around the GFC on the pre-crisis leverage ratio, their measure of firm-level credit constraint.[4] Our focus here is on the change in TFP growth and, subsequently, on the change in investment in intangibles as a potential explanation rather than the change in employment. Our baseline regression is as follows:

$$\Delta TFP^{growth}_{i,s,c} = \beta_1 Vulnerabilities^{pre}_i + \alpha_{s,c} + X_i\gamma + \epsilon_{i,s,c} \tag{4.1}$$

where $\Delta TFP^{growth}_{i,s,c}$ is the difference in average TFP growth of firm i, in sector s, and country c between the post-crisis (six years after the crisis 2008) and the pre-crisis (six years until 2008) periods. $Vulnerabilities^{pre}_i$ denote pre-crisis balance sheet vulnerabilities at the firm level discussed below, and X_i is a vector of firm-level controls including the age of the firm, log of its total assets and log of earnings (EBITDA) before the financial crisis. Our focus on the difference in firm-level TFP growth between two periods also means that all time-invariant firm characteristics that may affect TFP growth are implicitly controlled for. Standard errors are clustered at the country-sector.

The main variable we use to capture firm-level balance sheet vulnerabilities is the ex-ante rollover-risk, that is, the share of debt prior to the crisis that was scheduled to mature during the crisis, measured as the share of current liabilities (maturing within a year) at the end of 2007. This is in similar spirit as Almeida et al. (2011) who exploit heterogeneity in pre-crisis long-term debt maturity structure.

Given that we aim to identify the effects of financial frictions on productivity growth, a threat to our identification strategy could be that our measure of vulnerability does not only reflect financial frictions but is also correlated with other unobserved factors associated with the post-GFC slowdown − such as, for example, the quality of the firm's managers, or the sensitivity of demand for its products to overall cyclical conditions. For instance, if, within a given industry, product demand was more sensitive to a decline in aggregate demand for a more vulnerable firm than for its less vulnerable counterpart, we could overestimate the negative effect of vulnerabilities on productivity growth. However, because the September 2008 shock to credit conditions was unforeseen, it is plausible to assume that firms did not systematically schedule their debt to mature just before

[4]One advantage of comparing the six years after versus the six years before the crisis is that we allow for a dynamic TFP response instead of restricting it to be contemporaneous. Papers by Mian and Sufi (2014) and Khwaja and Mian (2008) are other examples of recent examples of approaches that collapse the data around events. See Bertrand et al. (2004) for a discussion of differences-in-differences strategies.

the crisis to avoid rollover risk.[5] Therefore, firms' debt structure prior to this event is unlikely to be correlated with other unobserved firm characteristics that might correlate with the magnitude of the decline in TFP growth post-crisis.

In addition, and crucially, our specification includes country-sector fixed effects. This implies that we compare the change in average TFP growth between more and less vulnerable firms within narrowly defined country-sector cells. This control is crucial because it is well established, for instance, that some sectors rely more heavily on external finance than others, and therefore exhibit higher leverage ratios (Rajan and Zingales, 1998). It could also be that firms' productivity in trade-intensive sectors in export-oriented countries may have suffered more than others from the trade slowdown after the crisis (Alcalá and Ciccone, 2004). Likewise, in certain countries the crisis-related decline in demand and its cyclical impact on measured productivity may have been greater in certain sectors, such as construction, than in others. Finally, policy changes such as tax, product or labor market reforms in some countries in the aftermath of the crisis might have affected productivity growth in certain sectors more than in others. By including country-sector fixed effects, we rule out that our results may be affected by such factors.

To further identify the impact of tighter credit conditions on the post-crisis decline in TFP growth in firms with pre-existing balance sheet vulnerabilities, we then exploit the fact that the magnitude of the credit supply shock that followed the collapse of Lehman Brothers on September 15th 2008 varied across countries. If balance sheet vulnerabilities indeed contributed to weaken within-firm TFP growth when credit conditions tightened, we should expect this effect to have been larger in countries where credit conditions tightened more. We test for this conjecture by augmenting our baseline regression (1) with an interaction term as follows:

$$\Delta TFP_{i,s,c}^{growth} = \beta_1 Vulnerabilities_i^{pre} + \beta_2 Vulnerabilities_i^{pre} * \Delta CDS_c + \alpha_{s,c} + X_i\gamma + \epsilon_{i,s,c} \tag{4.2}$$

where ΔCDS_c is the change in the average CDS spread of domestic banks in country c between the 7 days before and after the Lehman bankruptcy. In the week after Lehman's bankruptcy, CDS spreads rose as banks tried to protect themselves against defaults of other banks (Brunnermeier, 2009). All else equal, banks whose

[5] Cheng et al. (2014) show that even managers in the securitized finance industry failed to identify the housing bubble.

CDS spreads rose more around the collapse of Lehman Brothers experienced a larger increase in perceived vulnerabilities. These banks typically suffered a sudden erosion of bank capital and difficulties in obtaining funding on the interbank market (Afonso et al., 2011; Brunnermeier, 2009). These balance sheet constraints may have in turn induced them to restrict credit supply, with adverse effects on real outcomes (Chodorow-Reich, 2013; Ivashina and Scharfstein, 2010). By exploiting the change in CDS spreads over a narrow window around the Lehman bankruptcy, we can plausibly consider it as a shock to credit supply and rule out that it was driven by other factors. For instance, the increase in the CDS spread is unlikely to be the consequence of a real shock that affected firms and, through them, banks' riskiness, since in the week just after the bankruptcy, the consequences for the economy had not yet materialized. Therefore, we argue that a greater exposure to the Lehman bankruptcy, as reflected in a larger increase in domestic bank CDS spreads around September 15th 2008, captures an exogenous tightening of aggregate credit conditions for domestic firms in the country considered. Note that using the change in domestic bank CDS spreads as a measure of the tightening of credit conditions for domestic firms implicitly assumes that the latter rely heavily upon banks in their home country for their funding needs, and cannot fully tap other sources of credit as a substitute; we see this as a reasonable assumption given that our sample is dominated by small European firms that typically do not have access to corporate bond markets, syndicated lending or cross-border bank lending.

In a final extension, we further sharpen our identification strategy by making use of matched firm-bank credit relationship data. These allow us to exploit variation in the degree of tightening in credit conditions across firms within countries. An important source of firm-level variation in the tightening of credit conditions is that domestic firms relied on different creditor banks, which in turn were hit differentially by the Lehman shock. We exploit this heterogeneity by estimating:

$$\Delta TFP_{i,s,c}^{growth} = \beta_1 Vulnerabilities_i^{pre} + \beta_2 Vulnerabilities_i^{pre} * \Delta CDS_i + \beta_3 \Delta CDS_i + \alpha_i + X_i \gamma + \epsilon_{i,s,c} \tag{4.3}$$

where ΔCDS_i is now the change in the average CDS spread across firm i's main creditor banks.

4.2.2 Data and Stylized Facts

Our firm-level variables are drawn from ORBIS, a unique cross-country longitudinal dataset of both listed and unlisted firms provided by Bureau van Dijk. The dataset features harmonized and rich information on firms' productive activities (for instance, value-added output, capital stock, employment) and financial situation based on balance sheets and income statements (for instance, debt, assets, tangible and intangible fixed assets, long-term debt) from 1998 until 2013.[6]

We focus on 11 advanced economies for which we also have information on aggregate financial and credit conditions over this period, namely Belgium, Germany, Spain, France, Italy, Japan, Korea, the Netherlands, Portugal, Sweden, and the United Kingdom.[7] We study firms in the non-farm, non-financial business sector, which corresponds to the two-digit industry codes 5-82 in NACE Rev.2., covering both manufacturing and service sectors including for example real estate and profession/scientific/technical activities.[8]

To ensure consistency and comparability of monetary variables across countries and over time, we adopt the methodology followed in particular by Gal and Hijzen (2016). First, the original data recorded in USD are converted into local currency. Subsequently, nominal variables are turned into real variables by applying local currency deflators obtained from OECD STAN (ISIC4 version), which are rebased to 2005 US dollars using country-industry level PPPs obtained from Inklaar et al. (2005). In addition, we exclude very small firms (less than 3 employees), a common practice in studies using firm-level data, due to concerns regarding the reliability of the data as well as the consistency of variables over time.

The main dependent variable used in the analysis is revenue TFP growth, which we obtain by estimating a production function on firm-level data for each industry separately, following the approach of Wooldridge (2009). OLS regressions would

[6]See Gal (2013), Kalemli-Ozcan et al. (2015b) and Gal and Hijzen (2016) for a more detailed description of the dataset and the merging of different ORBIS vintages.

[7]Our empirical specification contains only firms that exist continuously during the 6 years before and after the GFC. This reduces the estimation sample significantly relative to the raw ORBIS dataset. Furthermore, the coverage of firms varies substantially across countries − a well-known feature of ORBIS, see e.g. Gopinath et al. (2017); Kalemli-Ozcan et al. (2015b). In the sample we use for the specifications that interact firm-level vulnerability with country-level CDS spreads, some countries have less than 500 firms (Germany, Portugal, the Netherlands for instance) while others have more than 10,000 firms (France, Spain, Sweden, Italy for instance).

[8]See here for further information on the categorization and correspondence with other sector classifications (http://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07-015-EN.PDF).

yield biased and inconsistent estimates of the production function coefficients, due to a simultaneity problem that has been known since at least Marschak and Andrews (1944). For example, more productive firms may employ more labor, which, because productivity is unobserved and enters the error term, will create a positive correlation between the error term and labor input. A remedy to this problem is the semi-parametric approach of Olley and Pakes (1996), which uses investment as a proxy variable for unobserved TFP to estimate the labor coefficient in the first stage of a GMM estimation procedure, and then the capital coefficient in a second stage. However, because investment is *lumpy*, it may be a poor proxy for productivity. At a more practical level, because many firms do not invest every year, this approach discards a non-trivial share of available observations and reduces sample size. These issues are addressed by Levinsohn and Petrin (2003), who take a similar approach but use intermediate inputs, rather than investment, as proxies. However, Ackerberg et al. (2015) stress that the control function used in the (first stage of the) semi-parametric approach and the coefficient on labor input are collinear, because both labor and intermediate inputs are decided in similar ways, simultaneously with unobserved productivity shocks. Wooldridge (2009) approach builds upon the Levinsohn and Petrin (2003) method but addresses the critique of Ackerberg et al. (2015), and also provides a more efficient one-step rather than two-step GMM estimation procedure. Therefore, this is the approach we adopt in the present paper.

The use of revenue productivity as in Gopinath et al. (2017), for example implies that firm-specific price variations within each sector affect our productivity estimates. While these can, all else equal, reflect quality changes, they can also reflect market power of the firm. If more resilient firms increased prices since the crisis, this would mechanically result in relatively higher measured productivity growth for these firms. However, since Gilchrist et al. (2017) show that financially constrained firms raised prices during the financial crisis, our results would be if anything, downward biased.[9]

Finally, we collect available daily CDS spread data for all individual banks and, for each of them, measure exposure to the September 15th 2008 Lehman collapse as the change in the average CDS spread between the week after and the week before September 15th. We derive from these bank-level data two indicators of tightening

[9]See also Syverson (2011) for a discussion of these pros and cons of using revenue-based productivity.

in credit conditions for firms, which enter equations (2) and (3) above, respectively. The first is a country-level indicator, which we compute as the simple average of changes in bank CDS spreads around the Lehman collapse across all domestic banks within a given country.[10] The second is a firm-level indicator, which is the simple average of changes in the CDS spreads of the firm's bank creditors. We compute it using the variable featured in AMADEUS, which lists for each firm up to five banks that are its most important credit providers. This variable has been used to identify firm-level financial shocks (originating from the matched banks) in several previous studies, including Giannetti and Ongena (2012), Kalemli-Ozcan et al. (2015a) and Barbiero et al. (2016).[11] We use the matched firm-bank data from the 2015 vintage, relying on the assumption put forward by Kalemli-Ozcan et al. (2015a) and Barbiero et al. (2016) that bank-firm relationships are sticky and do not vary much over time. This analysis entails a severe reduction in sample size, due to the unavailability of the BANKER variable for non-European countries, and the inexistence of CDS spreads for many of the matched banks. For these reasons, we treat specification (3) as an extension rather than as the core of our analysis, which instead consists of specifications (1) and (2).

Summary statistics for the dataset are provided in Table 4.1. It shows that the average firm experienced a large drop in TFP growth after the GFC, from 2.14 percent to -6.73 percent.[12] Our financial vulnerability variable shows substantial variation across firms. The amount of debt maturing in 2008 as a ratio of 2007 sales is 24.98% for the median firm, with a standard deviation of 21.52%.

Figure 4.1 shows the TFP level path for firms with different degrees of rollover risk at the onset of the crisis. Before the crisis, the figure shows that *weak* firms (solid lines) experienced just as strong productivity growth as *strong* firms (dotted lines). However, after 2008, trajectories diverged, as *weak* firms experienced a much sharper drop in productivity growth. It is worth noting that the large gap between weak and resilient firms that opens in 2009 is not closed by 2013 (the last available year in our sample), and indeed appears to keep on widening.

[10]Results are robust to considering the principal component of these spreads instead.

[11]The original source of this variable is Kompass. Kompass provides information on banks and firms over 70 countries, particularly establishing bank-firm relationships. See Giannetti and Ongena (2012) for further details.

[12]Since we only focus on within-firm TFP growth and smaller firms experienced a larger post-crisis drop in TFP growth than larger firms, these unweighted numbers are much larger than their weighted counterparts.

4.3 Empirical Results

This section first presents our productivity growth regression results, and then investigates the impact of financial frictions on intangible investment as one possible channel through which tighter credit conditions may have affected post-crisis TFP growth in more vulnerable firms. We start with estimates of our baseline regression (1) in Section 3.1. Section 3.2 turns to our extended specifications (2) and (3), which exploit the cross-country and cross-firm heterogeneity in the degree of tightening of credit conditions around the collapse of Lehman Brothers. In Section 3.3, we re-run our specifications replacing TFP growth by intangible investment, to test whether the latter was also affected by financial frictions. This enables us to establish a connection between the productivity slowdown and weaker intangible investment. Section 3.4 runs a placebo test that checks whether the effects of financial frictions vanish when focusing instead on the recession of the early 2000s − a recession that was not accompanied by a banking crisis.

4.3.1 Baseline regression results

Table 4.2 shows our baseline regression (equation 1) results for different sets of (country-, sector- and country-sector) fixed effects and with and without firm-level controls. Firms with more vulnerable balance sheets, as measured by a higher share of debt maturing in 2008, experienced a stronger decline in TFP growth. The estimated impact using our preferred specification including both country-sector fixed effects and firm-level controls (column (4)) is quantitatively large: a 10 percentage points higher share of debt maturing in 2008 was associated with a 0.94 percentage point drop in annual TFP growth in the post-crisis period.[13]

These results are illustrated graphically in Figure 4.3, which shows the implied difference in average TFP growth between pre- and post-crisis periods for firms at the 75th and 25th percentiles of the cross-firm distribution of the indicator of financial vulnerability (more and less vulnerable firms, respectively). While both types of firms experienced comparable TFP growth until 2008 (black bars), the post-crisis drop in TFP growth was much less in the former (grey bars) than in the latter (shaded bars).

[13]These results are quantitatively and statistically robust to controlling additionally for each firms' average rollover risk over the years 2003-2007. This further shows that our results are not driven by the fact that firms that had balance sheet vulnerabilities on the eve of the financial crisis were intrinsically weak firms that were structurally forced to raise short-term debt.

How much of the total (firm-level) TFP growth slowdown do these findings account for $-$ A rough back-of the-envelope calculation can provide an illustrative estimate. Let us assume conservatively that firms that did not have any debt maturing in 2008 did not face financial frictions, and therefore did not experience any related slowdown in TFP growth. Using the coefficient of debt maturity 2008 in column (4) of Table 4.2 (-0.094) and multiplying it by each firm's share of debt maturing in 2008 yields each firm's estimated TFP growth loss due to pre-existing financial vulnerabilities. We then aggregate each individual firm's TFP growth loss, using their value-added levels as weights, to derive the overall effect. This illustrative calculation yields an aggregate TFP growth loss of about 2.39 percentage points compared to a state in which there would have been no financial frictions. By comparison, the aggregate TFP growth drop observed in our sample, which can be calculated as the weighted sum of each firm's change in TFP growth between the pre- and post-crisis periods, is about of 6.37 percentage points. This tentatively suggests that the interplay between tighter credit conditions and firms' pre-existing financial vulnerabilities may account for some 37% ($\sim$ 2.39/6.37) of the total within-firm TFP growth loss after the GFC.

4.3.2 Extended specifications

Our baseline specification highlights the interplay between balance sheet vulnerabilities and the 2008 shock to credit conditions in driving down TFP growth post-crisis, but it does not recognize that the shock to credit conditions was in fact heterogenous across countries and firms. To remedy this and sharpen our identification strategy, this section provides estimates of our extended specifications (2) and (3).

Our main extended specification is (2), which tests for interactions between our measure of pre-crisis firm-level vulnerability and the change in the average CDS spread of domestic banks between the weeks before and after September 15th 2008. We standardize the CDS spread by first subtracting the sample mean and then dividing by the standard deviation. Hence, this variable takes value one when the CDS spread increase after the Lehman bankruptcy is one-standard-deviation (about 20 basis points) larger than in the average country in our sample. Standardizing the change in CDS also allows us to interpret the direct effect of firm-level vulnerabilities as their effect on the change in TFP growth in the average firm in the average country.[14]

The results, which are reported in Table 4.3, confirm the role played by tighter credit conditions in the post-crisis TFP slowdown. Firms with pre-existing balance sheet vulnerabilities experienced a larger drop in TFP growth (vis-à-vis their less vulnerable counterparts) in countries where credit conditions tightened more; interaction terms between both firm-level vulnerability measure and the country-wide change in bank CDS spreads are statistically significant at the 1% confidence level, as are the direct effects. Based on the results in column (4), in a country that experienced an average increase in bank CDS spreads, a 10 percentage points increase in the share of debt maturing in 2008 was associated with a 0.96 percentage point drop in annual TFP growth. In a country where the increase in CDS spreads was one standard deviation larger than the average country, the corresponding decline in TFP growth was 0.9 percentage points larger (0.9 $\sim$10*0.0897*1).

This cross-country heterogeneity is illustrated graphically in Figure 4.4, also using the estimates from column (4) in Table 4.3. The two bars compare the post-crisis decline in TFP growth for firms that lie on the 25th (low rollover risk) and 75th (high rollover risk) percentiles of the pre-crisis distribution of the share of debt maturing in 2008 for two hypothetical countries. These two hypothetical countries differ from one another by the degree of credit conditions tightening, namely, an average country is compared to a country with tighter credit conditions which experienced one standard deviation larger CDS spread around the Lehman bankruptcy. The difference is sizeable − a higher share of debt maturing in 2008 was associated with a substantially larger decline in post-crisis TFP growth in the country where CDS spreads increased more (right bar).

To further sharpen our identification strategy, we now estimate an extended specification (3) that interacts our measure of pre-crisis firm-level vulnerability with the change in the average CDS spread of the main creditor bank(s) of the firm considered between the weeks before and after September 15th 2008. As noted above, this comes at the cost of a severe reduction in sample size as not all firms report their creditors (see Kalemli-Ozcan et al. (2015b) for further details on the limitations of creditor information in certain countries). Nonetheless, the results, which are shown in Table 4.4, strengthen our key finding: firms with greater debt

[14]The difference in coefficients on the direct effects of vulnerabilities between Tables 2 and 3 can be explained partly by the fact that the coefficient in Table 4.2 captures the impact in the average firm (not necessarily in the average country) while the coefficient in Table 4.3 captures the impact in the average firm in the average country.

maturing in 2008 suffers a larger drop in TFP growth post-Lehman, and that drop was greater for firms that faced a more severe tightening of credit conditions (from their matched banks). The interaction of debt maturing in 2008 and the increase in the matched firm-bank CDS spread is negative and statistically significant at the 5% confidence level. It is also economically significant: a 10 percentage point larger ratio of debt maturing in 2008 was associated with a 1.63 percentage point larger decline in average annual TFP growth post-crisis for a firm whose main creditor bank(s) had an average exposure to Lehman, but with a 1.86 percentage points (1.63+0.23=1.86) larger decline in TFP growth for a firm's whose main creditor bank(s) faced an increase in CDS spreads that was one-standard-deviation larger than the average. While smaller than the implied impact from the specification with the country-wide CDS spread (equation (2)), this still amounts to a large cumulative impact of pre-crisis vulnerabilities on the TFP level over the 6 years after the GFC − keeping in mind that a 10 percentage point larger ratio is equivalent to just half a standard deviation of the cross-firm distribution of debt maturing in 2008. Finally, an increase in the CDS spread of the firm's main creditor bank(s), in and of itself, does not appear to affect TFP growth, as suggested by its statistically insignificant coefficient. This further confirms that it is the interplay between pre-existing firm-level vulnerability and tighter credit conditions, rather than tighter credit conditions per se, that mattered for the post-GFC TFP slowdown.

4.3.3 Financial Frictions and Intangible Investment

Having established that financial frictions mattered for the post-GFC TFP slowdown, we now turn to the question of why they did so. While we do not attempt to provide a comprehensive answer to this question, we explore the role of weaker intangible investment as one possible channel. A wide range of recent studies have linked investments in intangible assets with productivity since the influential work of Corrado et al. (2005, 2009). When hit by a financial shock, firms may adjust various types of investment differently depending on expected returns, risks and gestation periods (Holmstrom and Tirole, 1997; Matsuyama, 2007; Garcia-Macia, 2015; Ridder, 2016). While most forms of physical capital can be pledged as collateral to get a loan, intangible assets such as R&D or workforce training cannot. Furthermore, investments in intangible assets tend to translate more slowly into sales and to be riskier. Therefore, our hypothesis is that credit-constrained firms cut their investment in intangible assets, contributing in part to a sharper productivity slowdown after the crisis.

To explore this question, we follow the same difference-in-differences strategy used earlier, only that now the change in the investment rate in intangible assets replaces the change in TFP growth as our dependent variable. We define the investment rate in intangibles as the change in the stock of intangible assets divided by value added available in ORBIS. This is comparable in spirit to the investment rate expressed as a share of GDP in national accounts. Our baseline regression is as follows:

$$\Delta Int\_Investment_{i,s,c} = \beta_1 Vulnerabilities_i^{pre} + \alpha_{s,c} + X_i\gamma + \epsilon_{i,s,c} \tag{4.4}$$

Furthermore, we assess if firms cut investment in intangibles more than investment in physical capital by estimating the following regression:

$$\Delta Share\_Intangible_{i,s,c} = \beta_1 Vulnerabilities_i^{pre} + \alpha_{s,c} + X_i\gamma + \epsilon_{i,s,c} \tag{4.5}$$

which is analogous to equation (4) but now considering as dependent variable the change in the share of intangibles in total assets. Total assets are the sum of tangible (physical) and intangible fixed assets. Table 4.5 shows these results. First two columns use the investment in intangible assets as the dependent variable, while the latter two columns use the share of intangible investments as the dependent variable.

Columns (1) and (2) show that firms with more vulnerable balance sheets indeed cut their investment in intangible assets significantly more than their less vulnerable counterparts. Considering that investment rates are typically much lower for intangible assets than for tangible ones, the estimates are also economically significant. Based on the estimates in column (2), a 10 percentage points increase in the share of debt maturing in 2008 was associated with a 0.18 percentage point drop in the investment rate in intangibles.

In addition, as the results in columns (3) and (4) show, firms with more vulnerable balance sheets indeed reduced the share of intangibles in total assets more than their less vulnerable counterparts. Using the estimates in column (4) of Table 4.5, a 10 percentage point larger share of debt maturing in 2008 was associated with a 0.58 percentage point decline in the share of intangible assets.

4.3.4 Placebo Test

To confirm that our results reflect the peculiar nature of the GFC, which was associated with a massive credit supply shock, we run a placebo test under which we estimate the impact of firm-level financial vulnerabilities on the change in within-firm TFP growth after the 2000 recession that followed the burst of the dot-com bubble. Because this recession was not associated with a banking crisis, when re-running regressions (1) and (2) with 2000 instead of 2008 as the assumed crisis year, we should not find any statistically significant impact of the share of debt maturing in 2000 on the change in firm-level TFP growth between the pre- and post-2000 recession periods. This is indeed what comes out of Table 4.7, where none of coefficients reported in columns (1) $-$ (4) show any statistical significance.

These results are presented graphically in Figure 4.4. Unlike Figure 4.1 which showed starkly different post-crisis TFP growth paths for firms with different levels of pre-crisis financial vulnerabilities, Figure 4.4 shows no such difference around the 2000 recession $-$ which, although much milder than the post-GFC recession, was still associated with a large TFP decline after 2001 in our sample of firms. This is consistent with previous studies which show that recessions associated with banking crises tend to have a prolonged negative effect on investment and real GDP while regular recessions do not (Cerra and Saxena, 2008; Rioja et al., 2014). Our findings suggest that the role of financial frictions for TFP may be one channel through which financial crises have such a puzzling, permanent adverse effect on real GDP.

4.4 Robustness Checks

4.4.1 Labor Productivity

Given the methodological and data issues involved in measuring TFP, we confirm that our main result holds when using labor productivity instead. To this end, we re-run our baseline regression replacing the dependent variable with the change in labor productivity, measured as the ratio of real value-added output to the number of employees. Table 4.7 reports the results, which largely confirm those in Table 4.2 $-$ firms with greater financial vulnerabilities prior to the crisis experienced a sharper decline in labor productivity growth after the crisis. The magnitudes of the coefficients are also broadly in line with those in Table 4.2 $-$ a 10 percentage point higher share of debt maturing in 2008 was associated with a 0.5 percentage point further weaker average labor productivity growth rate in the post-crisis period.

4.4.2 Other Dimensions of Financial Vulnerability

We also check whether other dimensions of firms' financial vulnerability also affected post-crisis productivity growth, over and above the impact of our preferred rollover risk measure (debt maturing in 2008). To this end, we consider the following three additional variables: the ratio of cash and cash equivalents to total assets, a high value of which should reduce liquidity risk, all else equal; leverage, measured as the ratio of total liabilities to total assets; the interest coverage ratio (ICR), measured as the ratio of interest expenses to earnings, which captures the firm's ability to meet its interest payments. All three indicators are averaged over the pre-crisis period and included in our baseline regression, either separately or jointly. Table 4.9 shows the results. Most importantly, the coefficients of debt maturing in 2008 are highly stable across all specifications − the role of the random distribution of debt maturing in 2008 for post-crisis TFP growth is unaffected by the presence of different other measures of financial vulnerability. This is even though other dimensions of financial vulnerability also appear to have affected post-crisis TFP growth. All coefficients have the expected signs and are statistically significant, except for the cash ratio when all indicators are entered jointly in column (4).

4.4.3 GIIPS vs. Non-GIIPS

Firms in GIIPS countries (Greece, Ireland, Italy, Portugal and Spain) were on average more financially vulnerable than their counterparts in non-GIIPS countries coming into the financial crisis. Furthermore, banks in GIIPS countries were hit hardest, experiencing a bigger spike in their CDS spreads. Therefore, one would expect a more severe decline in productivity growth due to financial vulnerabilities in GIIPS countries. To test for this, we re-run our baseline regression for GIIPS non-GIIPS countries separately.[15] Table 4.9 shows that our baseline result holds for both samples. Furthermore, we find stronger effects of financial vulnerabilities affecting the post-crisis TFP growth in GIIPS countries compared to non-GIIPS countries − based on columns (3) and (4) in Table 4.9, a firm with a 10 percentage points higher share of debt maturing in 2008 experienced a 1.34 percentage point decline in TFP growth in GIIPS countries versus only 0.46 percentage point in non-GIIPS countries.

[15] Technically, our GIIPS sample only consists of Italy, Portugal and Spain since we do not have data for Greece and Ireland available.

4.4.4 Old firms vs. Young firms

Young and old firms may differ fundamentally in that the former may be forced to take up short-term debt for lack of alternative means of funding, while the latter may have more options and may therefore set their debt maturity more freely. In this robustness check, we check for any potential endogeneity issue due to firm age by splitting our sample in two bins − older firms and younger firms − and comparing the coefficients of each bin. Older (younger) firms are defined as those that are more (less) than 16 years old − the average firm age in our sample − in 2007. Table 4.11 reports the results. Our main finding appears to hold for both samples, while the coefficients of debt maturing in 2008 do not differ significantly between them when we group young and old firms together and interact a dummy for young with the share of debt maturing in 2008.

4.4.5 Interacting Controls with CDS spread changes

We also re-run our extended specification (2) with interactions between all the firm-level controls and the change in the average bank CDS spread around the Lehman shock. This is to further ensure the stability of our coefficients of interest to such controls. The results reported in Table 4.12. The estimated coefficients of debt maturing in 2008 and its interaction with the change in the average bank CDS spread are very similar to those in Table 4.3.

4.4.6 Controlling for the level of TFP prior to the crisis

In a final robustness check, we check for the robustness of our baseline results when controlling for the average level of TFP before the crisis. This is to address the potential concern that the post-crisis change in firm's TFP growth could be somehow related to its pre-crisis TFP level, which in turn may correlate with the firm's reliance on short-term debt. For example, it could be that firms that had higher short-term debt prior to the crisis were low-TFP-level firms that were catching up fast, and were thus bound to experience a gradual slowdown in their TFP growth regardless of the GFC. In practice, however, the data show no material link between the average TFP level and short-term debt prior to crisis. The correlation is -0.09, and the average pre-crisis TFP level of firms that were above the 75th percentile of the distribution of short-term debt was just 1.1 percent higher than that of firms that were below the 25th percentile. Reflecting this, controlling for the level of TFP does not affect our baseline results, as shown in Table 4.12.

4.5 Conclusion

In this paper, we have studied the impact of financial frictions on firm-level productivity. Using a rich cross-country, firm-level data set and exploiting variation in pre-existing firm-level exposure to the 2008 global financial crisis, we have shown that the interplay between pre-existing financial fragilities and tightening credit conditions weakened within-firm productivity growth after the crisis, and disproportionately so for firms that faced a more severe tightening of credit conditions. The resulting effect on TFP levels has been large and highly persistent. We have also provided evidence that more restrictive access to credit led more vulnerable firms to cut back on intangible investment expenditure. Future research should delve deeper into this and other channels through which credit conditions could affect productivity within firms.

	Mean	Median	P25	P75	Standard Deviation
ΔTFP^{growth}	-10.72	-8.78	-30.54	9.00	33.83
$\overline{TFP}^{growth}_{pre}$	2.14	2.82	-8.84	14.10	18.53
$\overline{TFP}^{growth}_{post}$	-6.73	-5.22	-17.89	4.02	17.13
Debt Maturing 2008	30.81	24.98	15.80	39.70	21.51
Observations	134838				

Note: ΔTFP^{growth} is the difference in the TFP growth rate post vs. pre-crisis. $\overline{TFP}^{growth}_{pre}$ is the average TFP growth rate pre-crisis. $\overline{TFP}^{growth}_{post}$ is the average TFP growth rate post-crisis. *Debt Maturing 2008* is the amount of debt maturing in 2008 divided by average total sales pre-crisis. The pre-crisis period ranges from 2002-2007. The post-crisis period ranges from 2008-2013.

Table 4.1: *Summary Statistics*

	(1)	(2)	(3)	(4)
Dependent variable:		ΔTFP^{growth}		
Debt Maturing 2008	-0.0693***	-0.0704***	-0.0674***	-0.0935***
	(0.007)	(0.006)	(0.006)	(0.008)
R-squared	0.127	0.131	0.142	0.151
N	134838	134838	134838	134838
Country*Sector FE	No	No	Yes	Yes
Sector FE	No	Yes	-	-
Country FE	Yes	Yes	-	-
Controls	No	No	No	Yes

Note: The dependent variable ΔTFP^{growth} is the difference in the average TFP growth rate between post- and pre-crisis periods. *Debt Maturing 2008* is the amount of debt maturing in 2008 divided by average total sales pre-crisis. The post-crisis period starts in 2008. Firm-specific controls include firm age, size of assets and earnings (EBITDA). Standard errors in parentheses. Standard errors are clustered at the country-sector level. *: significant at 10% level; **: significant at 5% level; ***: significant at 1% level.

Table 4.2: *Baseline Regression Results*

	(1)	(2)	(3)	(4)
Dependent variable:		ΔTFP^{growth}		
Debt Maturing 2008	-0.0706***	-0.0686***	-0.0682***	-0.0960***
	(0.007)	(0.006)	(0.006)	(0.007)
Debt Maturing 2008 $*$ ΔCDS_c	-0.0823***	-0.0781***	-0.0824***	-0.0897***
	(0.024)	(0.023)	(0.020)	(0.020)
R-squared	0.143	0.148	0.156	0.167
N	104275	104275	104275	104275
Country*Sector FE	No	No	Yes	Yes
Sector FE	No	Yes	-	-
Country FE	Yes	Yes	-	-
Controls	No	No	No	Yes

Note: The dependent variable ΔTFP^{growth} is the difference in the average TFP growth rate between the post- and pre-crisis periods. *Debt Maturing 2008* is the amount of debt maturing in 2008 divided by average total sales pre-crisis. The post-crisis period starts in 2008. ΔCDS_c is the standardized change in the country-level CDS between the weeks before and after the Lehman bankruptcy, where the change in the country-level CDS is calculated as an average of the changes in domestic banks' CDS spread over the same window. Firm-specific controls include firm age, size of assets and earnings (EBITDA). Standard errors in parentheses. Standard errors are clustered at the country-sector level. *: significant at 10% level; **: significant at 5% level; ***: significant at 1% level.

Table 4.3: *Extended Specification: Accounting for Cross-Country Heterogeneity in Exposure to the Collapse of Lehman Brothers*

	(1)	(2)	(3)	(4)
Dependent variable:		ΔTFP^{growth}		
Debt Maturing 2008	-0.115***	-0.112***	-0.114***	-0.163***
	(0.014)	(0.015)	(0.015)	(0.015)
ΔCDS$_i$	-0.140	-0.179	-0.176	-0.293
	(0.214)	(0.219)	(0.217)	(0.214)
Debt Maturing 2008 $*$ ΔCDS$_i$	-0.0232**	-0.0244**	-0.0243**	-0.0228**
	(0.010)	(0.010)	(0.010)	(0.011)
R-squared	0.0637	0.0719	0.0793	0.109
N	20798	20798	20798	20798
Country*Sector FE	No	No	Yes	Yes
Sector FE	No	Yes	-	-
Country FE	Yes	Yes	-	-
Controls	No	No	No	Yes

Note: The dependent variable ΔTFP^{growth} is the difference in the average TFP growth rate between post- and pre-crisis periods. *Debt Maturing 2008* is the amount of debt maturing in 2008 divided by average total sales pre-crisis. The post-crisis period starts in 2008. ΔCDS$_i$ refers to the standardized change in the average CDS spread of the firm's main creditor bank(s) (up to five of them, drawn from the $BANKER$ variable in AMADEUS) between the weeks before and after the collapse of Lehman Brothers. Firm-specific controls include firm age, size of assets and earnings (EBITDA). Standard errors in parentheses. Standard errors are clustered at the country-sector level. *: significant at 10% level; **: significant at 5% level; ***: significant at 1% level.

Table 4.4: *Extended Specification: Accounting for Firm-Level Heterogeneity in Exposure to the Collapse of Lehman Brothers*

	(1)	(2)	(3)	(4)
Dependent variable:	$\Delta Int\_Investment$		$\Delta Share\_Intangible$	
Debt Maturing 2008	-0.0188***	-0.0184***	-0.0633***	-0.0584***
	(0.002)	(0.002)	(0.010)	(0.010)
R-squared	0.0406	0.0407	0.373	0.379
N	97487	97487	101150	101150
Country*Sector FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

Note: The dependent variable $\Delta Int\_Investment$ for Columns (1) and (2) is the difference in the investment in intangible assets as a ratio of value added post vs. pre-crisis. The dependent variable Δ*Share_Intangible* for Columns (3) and (4) is the difference in the share of intangible assets in total capital post vs. pre-crisis. *Debt Maturing 2008* is the amount of debt maturing in 2008 divided by average total sales pre-crisis. The post-crisis period starts in 2008. Firm-specific controls include firm age, size of assets and earnings (EBITDA). Standard errors in parentheses. Standard errors are clustered at the country-sector level. *: significant at 10% level; **: significant at 5% level; ***: significant at 1% level.

Table 4.5: *Financial Frictions and Investment in Intangible Assets*

	(1)	(2)	(3)	(4)
Dependent variable:	ΔTFP^{growth} (post-2000 minus pre-2000)		$\Delta Int\_Investment$ (post-2000 minus pre-2000)	
Debt Maturing 2000	-0.0719	-0.0152	0.00483	0.00496
	(0.046)	(0.031)	(0.033)	(0.028)
R-squared	0.170	0.204	0.104	0.105
N	53139	53139	3295	3295
Country*Sector FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

Note: The placebo post-crisis period runs from 2000 until 2005, with 2000 assumed to be the crisis year. The dependent variable ΔTFP^{growth} is the difference in the average TFP growth rate between the post- and pre-crisis periods. The dependent variable $\Delta Int\_Investment$ is the difference in the investment in intangible assets as a ratio of value added post vs. pre-crisis. *Debt Maturing 2000* is the amount of debt maturing in 2000 divided by average total sales pre-2000. Firm-specific controls include firm age, size of assets and earnings (EBITDA). Standard errors are in parentheses. Standard errors are clustered at the country-sector level. *: significant at 10% level; **: significant at 5% level; ***: significant at 1% level.

Table 4.6: *Placebo Test: Early 2000s Recession*

	(1)	(2)	(3)	(4)
Dependent variable:		ΔLabor Productivity		
Debt Maturing 2008	-0.0515***	-0.0556***	-0.0428***	-0.0501***
	(0.006)	(0.006)	(0.005)	(0.005)
R-squared	0.0130	0.0192	0.0349	0.0383
N	106424	106424	106395	106395
Country*Sector FE	No	No	Yes	Yes
Sector FE	No	No	-	-
Country FE	Yes	Yes	-	-
Controls	No	No	No	Yes

Note: The dependent variable Δ*Labor Productivity* is the difference in the labor productivity growth rate post vs. pre-crisis. *Debt Maturing 2008* is the amount of debt maturing in 2008 divided by average total sales pre-crisis. Post-crisis starts in 200. Firm-specific controls include firm age, size of assets and earnings (EBITDA). Standard errors in parentheses. Standard errors are clustered at the country-sector level. *: significant at 10% level; **: significant at 5% level; ***: significant at 1% level.

Table 4.7: *Baseline Regression: Labor Productivity*

	(1)	(2)	(3)	(4)
Dependent variable:		ΔTFP^{growth}		
Debt Maturing 2008	-0.0900***	-0.0907***	-0.0917***	-0.0907***
	(0.007)	(0.007)	(0.007)	(0.007)
Cash Pre-Crisis	0.0284***			0.000564
	(0.007)			(0.008)
Leverage Pre-Crisis		-0.0363***		-0.0229***
		(0.008)		(0.009)
ICR Pre-Crisis			-0.0236***	-0.0193***
			(0.005)	(0.005)
R-squared	0.151	0.151	0.158	0.158
N	133272	134838	117882	116441
Country*Sector FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Note: The dependent variable ΔTFP^{growth} is the difference in the average TFP growth rate between the post- and pre-crisis periods. *Cash Pre-Crisis* is the ratio of average cash and cash equivalents to total assets before the crisis. *Leverage Pre-Crisis* is average leverage, measured as the debt-to-asset ratio, before the crisis. *ICR Pre-Crisis* is the average ratio of interest expenses to earnings (EBITDA), that is, the inverse of the interest coverage ratio, before the crisis. Firm-specific controls include firm age, size of assets and earnings (EBITDA). Standard errors are in parentheses. Standard errors are clustered at the country-sector level. *: significant at 10% level; **: significant at 5% level; ***: significant at 1% level.

Table 4.8: *Baseline Regression: Incorporating Other Measures of Financial Vulnerability*

	(1)	(2)	(3)	(4)
Dependent variable:	ΔTFP^{growth}			
	GIIPS	Non-GIIPS	GIIPS	Non-GIIPS
Debt Maturing 2008	-0.131***	-0.0521***	-0.134***	-0.0456***
	(0.009)	(0.009)	(0.009)	(0.008)
R-squared	0.0955	0.0384	0.106	0.0543
N	56223	78615	56223	78615
Country*Sector FE	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes

Note: The dependent variable ΔTFP^{growth} is the difference in the average TFP growth rate between the post- and pre-crisis periods. *Debt Maturing 2008* is the amount of debt maturing in 2008 divided by average total sales pre-crisis. Post-crisis starts in 2008. Firm-specific controls include firm age, size of assets and earnings (EBITDA). Column (1) and (3) considers only firms in GIIPS countries (Greece, Ireland, Italy, Portugal and Spain). Column (2) and (4) excludes firms in GIIPS countries. Standard errors are in parentheses. Standard errors are clustered at the country-sector level. *: significant at 10% level; **: significant at 5% level; ***: significant at 1% level.

Table 4.9: *Baseline Regression: GIIPS countries vs. Non-GIIPS*

	(1)	(2)	(3)	(4)
Dependent variable:	ΔTFP^{growth}			
	Old Firms	Young Firms	Old Firms	Young Firms
Debt Maturing 2008	-0.0647***	-0.0725***	-0.0823***	-0.105***
	(0.009)	(0.008)	(0.01)	(0.009)
R-squared	0.183	0.127	0.193	0.138
N	48827	85859	48827	85859
Country*Sector FE	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes

Note: The dependent variable ΔTFP^{growth} is the difference in the average TFP growth rate between the post- and pre-crisis periods. Old (young) firms are firms with the age older (less) than 16 years in 2007. Firm-specific controls include firm age, size of assets and earnings (EBITDA). Standard errors are in parentheses. Standard errors are clustered at the country-sector level. *: significant at 10% level; **: significant at 5% level; ***: significant at 1% level.

Table 4.10: *Baseline Regression: Old firms vs. Young firms*

	(1)	(2)	(3)
Dependent variable:		ΔTFP^{growth}	
Debt Maturing 2008	-0.0900***	-0.0956***	-0.0951***
	(0.008)	(0.007)	(0.007)
Debt Maturing 2008$*\Delta CDS_c$	-0.115***	-0.105***	-0.113***
	(0.025)	(0.024)	(0.021)
R-squared	0.156	0.161	0.169
N	104275	104275	104275
Country*Sector FE	No	No	Yes
Sector FE	No	Yes	-
Country FE	Yes	Yes	-
Controls	Yes	Yes	Yes

Note: The dependent variable ΔTFP^{growth} is the difference in the average TFP growth rate between the post- and pre-crisis periods. ΔCDS_c is the standardized change in the country-level CDS between the weeks before and after the Lehman bankruptcy, where the change in the country-level CDS is calculated as an average of the changes in domestic banks' CDS spread over the same window. Firm-specific controls include firm age, size of assets, employment and earnings (EBITDA). Each specification also includes interactions between each of these controls and ΔCDS_c. Standard errors are in parentheses. Standard errors are clustered at the country-sector level. *: significant at 10% level; **: significant at 5% level; ***: significant at 1% level.

Table 4.11: *Productivity Growth and Controls Interacted with CDS changes*

	(1)	(2)	(3)	(4)
Dependent variable:		ΔTFP^{growth}		
Debt Maturing 2008	-0.0698***	-0.0670***	-0.0629***	-0.0899***
	(0.006)	(0.005)	(0.005)	(0.006)
Average TFP level pre-crisis	-0.0641	0.637	0.860	0.595
	(0.419)	(0.655)	(0.673)	(0.609)
R-squared	0.127	0.131	0.142	0.151
N	134838	134838	134838	134838
Country*Sector FE	No	No	Yes	Yes
Sector FE	No	Yes	-	-
Country FE	Yes	Yes	-	-
Controls	No	No	No	Yes

Note: The dependent variable ΔTFP^{growth} is the difference in the average TFP growth rate between the post- and pre-crisis periods. *Average TFP level pre-crisis* is the average firm-level TFP level (measured by the Wooldridge method) before the crisis. Firm-specific controls include firm age, size of assets, employment and earnings (EBITDA). *: significant at 10% level; **: significant at 5% level; ***: significant at 1% level.

Table 4.12: *Controlling for the pre-crisis TFP level*

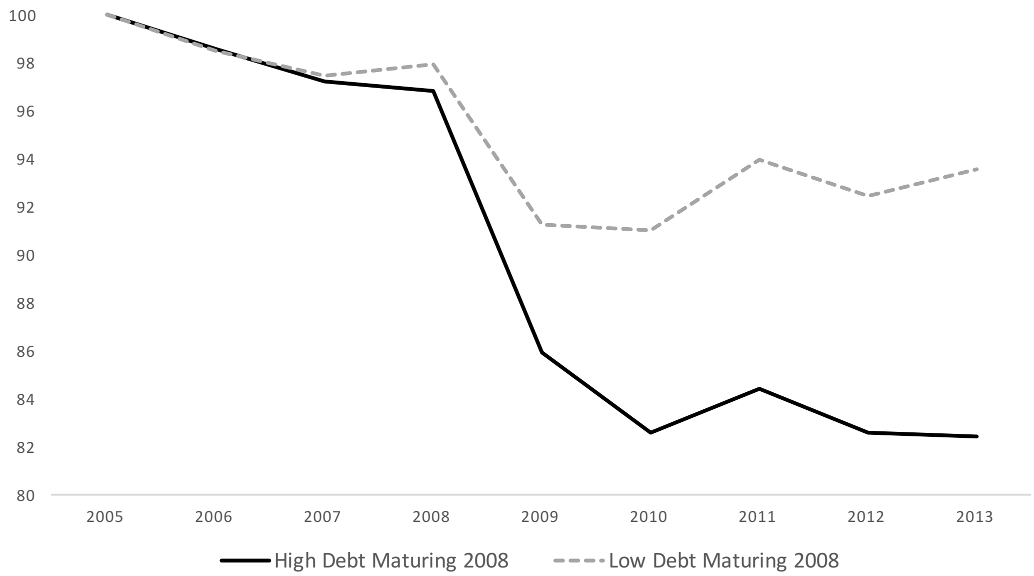

Figure 4.1: *TFP Level Path for Firms with Different Rollover Risks (Index 100 = 2005)*

Note: The TFP level path is shown as an index taking value 100 in 2005. *High Debt Maturing 2008* corresponds to the 75th percentile of the distribution of *Debt Maturing 2008*. *Low Debt Maturing 2008* corresponds to the 25th percentile of the distribution of *Debt Maturing 2008*. *Debt Maturing 2008* is the amount of debt maturing in 2008 divided by average total sales pre-crisis.

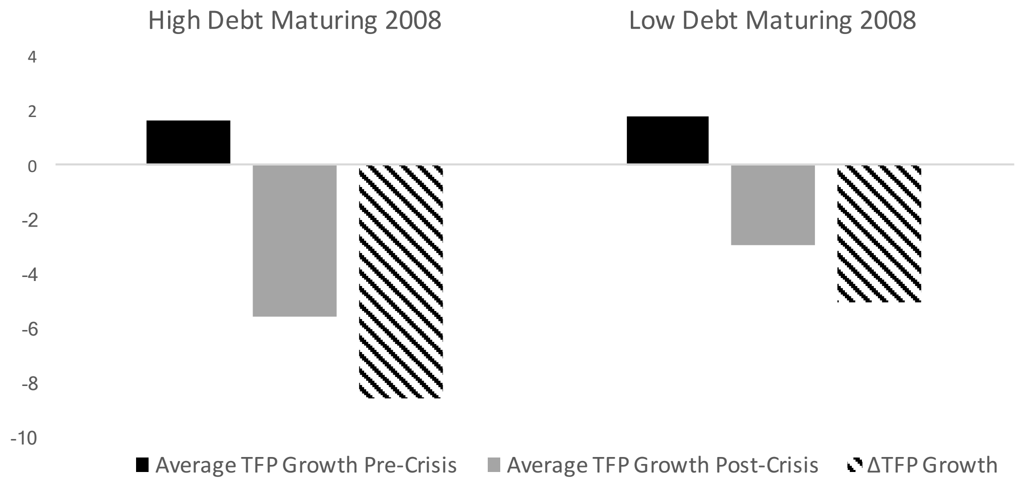

Figure 4.2: *Estimated TFP Growth Decline for Firms with Different Rollover Risks*

Note: ΔTFP^{growth} is the difference in the average TFP growth rate between the post- and pre-crisis periods. *Average TFP Growth Pre (Post) -Crisis* is the average TFP growth rate pre-crisis (post-crisis). *Debt Maturing 2008* is the amount of debt maturing in 2008 divided by average total sales pre-crisis. *High (Low) Debt Maturing 2008* corresponds to the 75th percentile (25th percentile) of the cross-firm distribution of *Debt Maturing 2008*. The post-crisis sample starts in 2008. The underlying regression estimates are those in column (4) of Table 4.2.

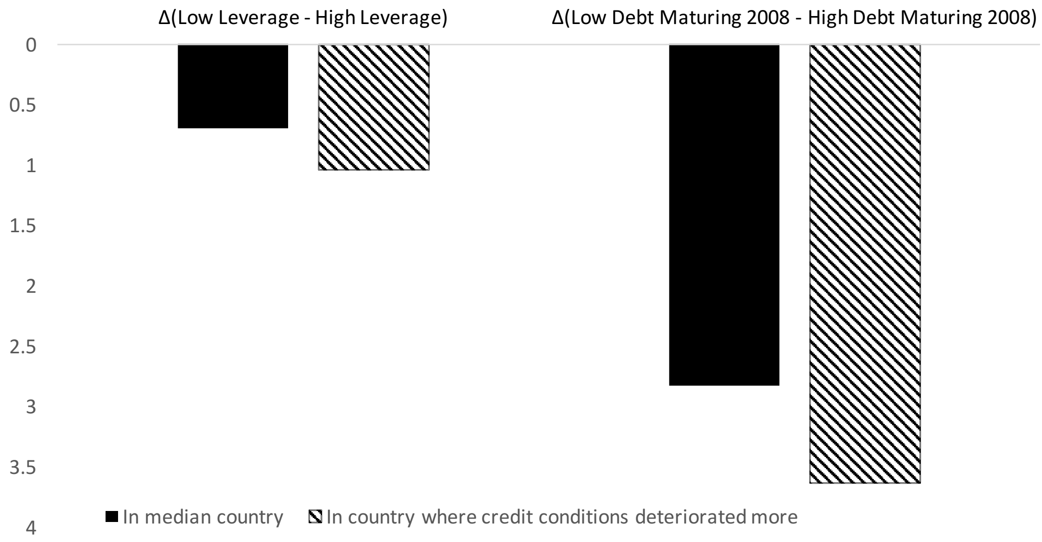

Figure 4.3: *Estimated TFP Growth Decline for Firms with Different Rollover Risks: The Role of Country Exposure to the Collapse of Lehman Brothers*

Note: *Rollover Risk* is the amount of debt maturing in 2008 divided by average total sales pre-crisis. *High (Low) Debt Maturing 2008* corresponds to the 75th (25th) percentile of the cross-firm distribution of *Debt Maturing 2008*. The *average country* corresponds to a no change in CDS spread after standardizing the variable. The *country where credit conditions deteriorated more* corresponds to one standard deviation larger change in standardized CDS spread compared to the average country CDS spreads. The post-crisis sample starts in 2008. The underlying regression estimates are those in column (4) of Table 4.3.

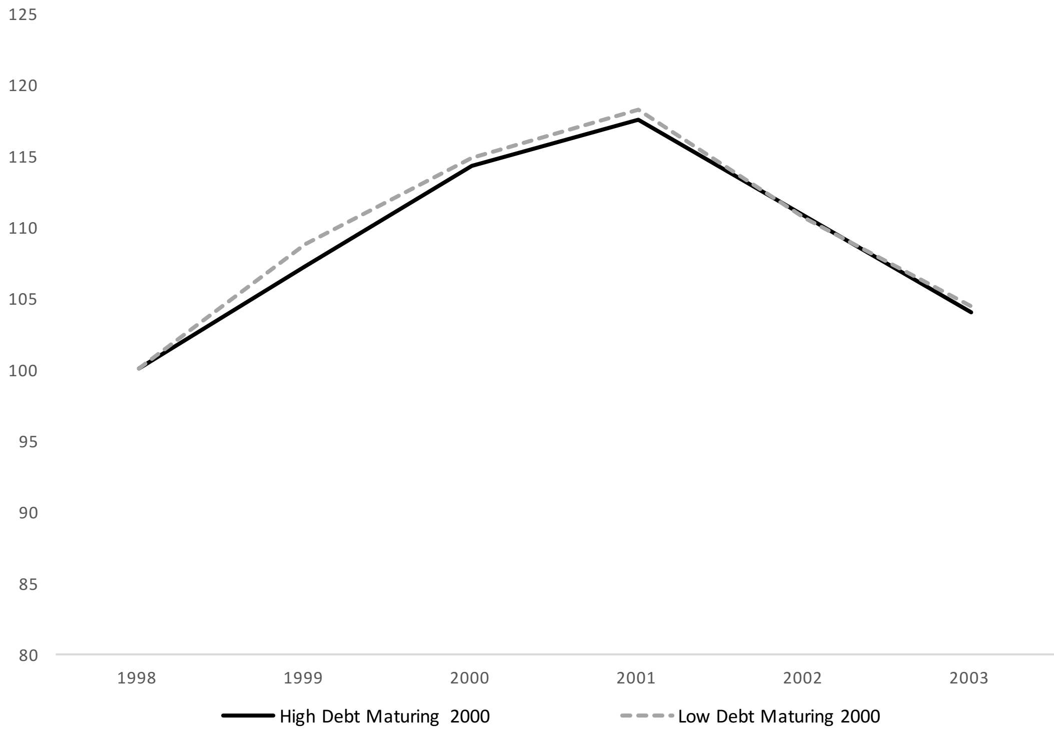

Figure 4.4: *TFP Level Path for Firms with Different Rollover Risks: 2000 Recession (Index 100 = 1998)*

Note: The TFP level path is shown as an index taking value 100 in 1998. *High (Low) Debt Maturing in 2000* corresponds to the 75th (25th) percentile of the cross-firm distribution of *High Debt Maturity 2000*. *Debt Maturing 2000* is the amount of debt maturing in 2000 divided by average total sales pre-2000.

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Chapter 5

General Conclusion

This thesis sheds light on different aspects of the global financial system and lies within the field of empirical financial economics and macroeconomics. Specifically, the three essays examine the global financial system from an academic perspective using newly available microeconomic data.

The first essay stresses the heterogeneity of different institutional investors in financial markets, while the second one explores heterogeneity across non-financial firms and their link to banks in derivative markets. The third essay focuses on the effect of heterogenous exposures of non-financial firms to financial frictions and the impact on the macroeconomy. So, the three essays are all linked in the sense that they stress heterogeneity across different actors in the global financial system using micro-economic data which is necessary to explore this heterogeneity.

Until relatively recently, empirical macroeconomists focused mostly on aggregates and paid little attention to the effect of heterogeneity within each country on the macroeconomy. Using heterogeneity can be a valuable way to shed light on the mechanism that is driving the aggregate behavior of macroeconomic outcomes. Both the failure to realize the theoretical significance of heterogeneity and the lack of data contributed to this phenomenon.

In light of tighter financial regulation in recent years more data has become available to explore the role of heterogeneity in finance and its impact on the real economy. In chapter 2, I depart from the assumption that all institutional investors exhibit the same investment behavior on capital markets and I show there are significant differences in the investment behavior across financial institutions.

It is shown that banks and investment funds exhibit a pro-cyclical investment behavior, i.e. they buy securities after price increases and sell securities after price declines. The opposite is the case for insurance companies and pension funds. The differential behavior across financial institutions can be attributed to the balance sheet constraints the institutions face. While banks' and investments funds' financial constraints are sensitive to losses on their security holdings, this is not the case for insurance companies and pension funds. Given that security prices exhibit a short-term momentum and a medium-term reversal component, the investment behavior of banks and investment funds can be rationalized. Since banks' and investment funds' financial constraints tighten when they suffer losses on their security holdings and they are averse against a tighter financial constraint, the short-term momentum component of security prices can incentive banks and investment funds to act pro-cyclically.

The findings indicate that macro-financial models should depart more and more from the representative agent model and should take into account that investor heterogeneity can play an important role for macroeconomic outcomes. Specifically, since banks and investment funds can destabilize the market, borrowers (both corporates and governments) should monitor their investor base. If their investor base consists mainly of banks and investment funds, borrowers should be cautious as the yield on their issued debt instruments can exhibit higher volatility.

In addition, the results have important implications for financial regulation. Since my results suggest that tighter financial constraints are driving more pro-cyclical investment behavior and pro-cyclical investment behavior can destabilize asset prices, policy makers should consider how financial regulation can affect the investment behavior. Macro-prudential regulation that pushes financial institutions further away from their financial constraints may have a containing effect on the pro-cyclical investment behavior. In contrast, micro-prudential regulation can induce pro-cyclical investment behavior for institutions that may naturally behave counter-cyclically. For instance, under the recently introduced Solvency II framework insurance companies are forced to mark to market their security holdings which may push these institutions closer to their financial constraints and makes them act in a pro-cyclical way.

However, while my results do suggest that tighter financial constraints are associated with more pro-cyclical investment behavior, the effect of regulation on the investment behavior is not the focus of this thesis. More work is needed in order to understand the relation between financial regulation and the investment behavior of financial institutions.

While recently introduced regulations like the Volcker rule, that prevents banks from engaging in proprietary trading are one option to regulate actors in financial markets, regulation that changes the constraints of institutions either intentionally or unintentionally can have more nuanced consequences.

In future work, it is important to understand not only how different financial institutions act on the debt capital markets but also how their risk-taking behavior is different across times. For example, how is the risk allocated across institutions in different times? Are insurance companies, who most closely resemble the rational long lived agents of our models, the ones that take the risk in bad times? Is this efficient and how does new regulation for insurance companies affect the outcome? Also, what is the role of insurance companies as the marginal investor compared to households, banks or investment funds? In order to answer these questions, it is important to not only consider the holdings of debt securities but also take into account other parts of the balance sheet of financial intermediaries.

Despite their high relevance in the economy, academic research on insurances is limited compared to research on banks and investment funds. Therefore, there are important topics to be investigated. For instance, how do insurance companies change their behavior in a low interest rate environment? How do insurance companies cope with the challenge that they insure aggregate risk and not only idiosyncratic risk anymore? How does micro-prudential regulation, like Solvency II, affect the stability of insurance companies and their usually stabilizing investment behavior? If micro-prudential regulation reduces the stabilizing role of insurance companies, there is a tradeoff between solvency of insurance companies and financial market volatility that needs to be evaluated. In addition, if micro-prudential regulation turns insurance companies to pro-cyclical investors, this raises the question of who is taking over the usually stabilizing role of insurance companies. While potential counter-cyclical investors are hedge funds due to their more risk-loving nature, more research is needed in order to understand who is on the other side of the trade.

As in chapter 2, chapter 3 makes use of newly available regulatory data to explore the issue of heterogeneity in financial markets. While chapter 2 focuses exclusively on financial institutions, the focus of 3 is on non-financial corporates and their trading behavior with banks. While non-financial corporates' main expertise is naturally not related to finance, these firms may also engage in financial markets transactions. Many companies have exchange rate exposure because they import or export goods in other currencies. In order to hedge this exposure, non-financial firms engage in foreign exchange forward transactions in the bilateral over-the-counter market. My co-authors and I show that non-financial corporates exhibit substantial price discrimination in these over-the-counter foreign exchange forward transactions with banks. We can attribute part of this price discrimination to the financial sophistication of the firm by making use of the range of firms that engage in these transactions. While many very sophisticated non-financial corporates are using foreign exchange forward transactions, even very unsophisticated companies have unwarranted exchange rate exposure which they demand to hedge in derivative markets. We use various proxies of sophistication of the non-financial company and we provide evidence that the more sophisticated the firm is, the less it is discriminated against.

Over the past years multi-dealer RFQ platforms of OTC FX deals have become increasingly popular. This trend reduces search costs and opacity frictions, gives rise to price competition, and allows firms, essentially SMEs, to find customized financial products. Such platforms allow non-financial clients to better hedge their cash flow related to international business and at a lower financial cost. Overall, trading RFQ platforms provides improved execution quality for these firms. This greatly enhances the attractiveness of FX risk hedging and contributes to a reduction of financial risk in the real sector.

One question that arises naturally is whether price discrimination discourages non-financial firms to enter the market. While we have collected anecdotal evidence that supports this hypothesis, more academic work is necessary to test this claim. If price discrimination leads to "under-hedging", it can have consequences for the macroeconomy. If a firm that has substantial exchange rate exposure and does not hedge the exposure, movements in the exchange rate can have detrimental effects on their profits and therefore macroeconomic volatility.

Future research may involve the combination of the Securities Holdings Statistics which I am using in chapter 2 and the EMIR dataset that is used in chapter 3. This can help us to understand a variety of different questions. For instance, do insurance companies engage in duration matching by using interest rate derivatives? Do banks use CDS to hedge credit risk of securities they already hold, or do they double-up their credit risk by selling CDS? Similarly, for sovereign exposures: In how far are we overestimating or underestimating the exposure of sovereigns if we do not consider their CDS positions?

While chapter 2 and chapter 3 focus mainly on financial markets, chapter 4 aims to link finance to the macroeconomy. We ask the question whether the low productivity growth in the aftermath of the 2008 financial crisis can be explained by a financial perspective. In particular, we show that non-financial firms that had more vulnerable balance sheets when the crisis hit, suffered lower productivity growth.

A back of the envelope calculation suggests that the effect of corporate financial vulnerabilities can account for about one third of the post-crisis within-firm productivity growth slowdown. One potential channel through which corporate financial vulnerabilities can undermine productivity growth is through investment in intangible assets, like research and development or software. In order to test this channel, we repeat the same analysis but replace productivity growth with investment in intangible assets and we indeed find that firms that had more debt maturing in the crisis reduced their intangible investment by more.

Since the interaction between weak corporate balance sheet and tightening credit conditions can undermine productivity growth this should be taken into account when central bankers decide on future path of monetary policy. A sharp increase in interest rates can tighten credit conditions and undermine productivity growth for firms with weak corporate balance sheets. This suggest that a sharp increase in interest rates should be avoided if central banks aim to avoid detrimental effects on productivity.

In addition, boosting investment on high-return projects can be one potential way how to support higher productivity growth. Since the investment in intangible assets is one way how corporate financial vulnerabilities can undermine productivity, countercyclical subsidies for investment in intangible assets may be a way to mitigate the effect of corporate financial vulnerabilities on productivity growth.