

BANKING, REAL ESTATE MARKETS AND MACROPRUDENTIAL POLICY:
QUANTITATIVE STUDIES AND EMPIRICAL SUPPORT

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By

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ABSTRACT

This dissertation studies frictions in the lending market that generate overlending and lax lending standards. Chapter 2 develops a quantitative model to study two frictions: 1) limited liability and 2) banks failing to internalize that their credit decisions alter the pool of borrowers faced by other banks, which is more pronounced in competitive lending environments. These frictions amplify the effects of economic fluctuations. I show that macroprudential policy tools, including capital requirements and taxes on banks' lending and borrowings, can encourage banks to screen more and should be state-contingent. I then gather panel data from the U.S. mortgage market to study the effect of competition on mortgage lending standards. I find that more competitive lending environments are associated with lower lending standards, which supports the model's conclusions. Moreover, I find that this relationship changes with the supply elasticity of housing.

Chapter 3 presents a quantitative model that incorporates two frictions: 1) limited liability, and 2) imperfect information about the persistence of asset price growth, which generates incorrect but rational lender beliefs. I calibrate the model to match recent credit boom-bust episodes and study which patterns of real estate price growth could serve as early warning indicators of a crisis. I then propose a Value-at-Risk rule to implement capital requirements. Capital requirements should be state-contingent and lean against lenders' beliefs by tightening after periods of asset price growth. However, the relationship between asset price growth and financial risk is not monotone,

and this should be incorporated in the setting of policy and interpretation of early warning indicators.

In Chapter 4, I create a new Metropolitan Statistical Area (MSA) level database to test the role of lender beliefs about housing prices and borrower incomes on mortgage lending standards. I employ a new proxy—banks’ local branching decisions—to capture lenders’ beliefs. I find that banks opening new branches in an MSA also lower their denial rates on mortgage applications associated with properties in that MSA. Moreover, I find that banks reacting to positive changes in home prices or borrower incomes by more rapidly expanding their branch network also approve more mortgage applications.

INDEX WORDS: Banks, Overlending, Lending Standards, Macroprudential Policy, Mortgage Lending, Bank Competition, Imperfect Information, Limited Liability

DEDICATION

To my family and my fiancé. Thank you for your love, support and encouragement. I could not have done this without you.

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CHAPTER 1

INTRODUCTION

Periods of rapid credit growth and lax lending standards often precede financial crises. Following the crisis of 2007-2008, there is a regulatory focus on restraining financial institutions from excessively extending credit. This dissertation studies three frictions in the lending market that generate overlending and lax lending standards and addresses how macroprudential policy tools can alleviate them. To conduct this research agenda, I do two things. First, I develop quantitative macro-banking models to study the three frictions, their effects and their policy implications. Second, I use panel data from the U.S. mortgage market to investigate whether the conclusions I find using my models are supported by the data. The first friction I study is limited liability of bank shareholders, which induces moral hazard and arises due to deposit insurance or government guarantees. The second friction I investigate is banks failing to internalize that their credit decisions alter the pool of borrowers faced by other banks, which is more pronounced in competitive lending environments. Third, I study the effects of imperfect information about the persistence of asset price growth, which generates incorrect but rational lender beliefs.

Chapter 2 can be divided into two parts. First, I develop a quantitative model with banks and borrowers to study the limited liability and lack of internalization frictions. Limited liability truncates bankers' return functions, leading them to take on more risk than they would if they were subject to incurring all losses. Likewise,

the lack of internalization friction causes banks to not fully internalize the market-wide impact of their actions and induces more risk-taking than a case where banks take their impact into account. These frictions lead banks to devote too few resources to screening their borrowers and amplify the effects of economic fluctuations. I find that the limited liability friction induces 27% excess volatility in output and that the lack of internalization friction leads to 8% excess output volatility. I show that employing macroprudential policy tools, including capital requirements and taxes on banks' lending and borrowings, can encourage banks to screen more and should be state-contingent, as the frictions' effects increase during business cycle expansions. Moreover, I find that taxes are the better policy tool in quantitative terms, as they do not reduce the amount of credit going to more productive borrowers.

Second, I gather panel data from the U.S. mortgage market to study the effect of competition on mortgage lending standards. When bank competition is measured by a Herfindahl-Hirschman Index (HHI) based upon bank branch market shares, I find support for the lack of internalization friction's implication that competition has a negative effect on lending standards. In addition, I find that this effect is stronger in markets that have an inelastic housing supply.

Chapter 3 presents a quantitative model of lenders and borrowers that incorporates the limited liability and imperfect information frictions. Limited liability again truncates lenders' return functions and induces risk-taking. With imperfect information, lenders cannot perfectly anticipate how persistent asset prices will be, so in order to make decisions they must form expectations about the underlying persistence using Bayes' rule. Because lenders may incorrectly interpret a transitory asset price shock as a shock to the trend, lenders may have episodes of incorrect but rational beliefs in which optimistic (pessimistic) expectations lead them to take on too much (little) risk.

After calibrating the model, I show that it can match recent credit boom-bust episodes. Next, I study which patterns of real estate price growth could serve as early warning indicators of a crisis. I find that the relationship between asset price growth and financial system risk is not monotone, and this should be considered in the setting of policy and interpretation of early warning indicators. I then propose a Value-at-Risk (VaR) rule to implement capital requirements. The VaR framework ensures that the probability of banks not having enough equity to cover their losses is maintained at a certain level. I find that capital requirements should be state-contingent and lean against lenders' beliefs by tightening after periods of asset price growth.

In Chapter 4, I create a new Metropolitan Statistical Area (MSA) level database using data from the Home Mortgage Disclosure Act (HMDA) and the FDIC's Summary of Deposits Survey to study the role of lender beliefs about housing prices and borrower incomes in mortgage approval decisions. The motivation for this exercise comes from the implications of imperfect information discussed in Chapter 3. Specifically, I employ a new proxy—banks' local branching decisions—to capture lenders' beliefs and examine whether I can identify evidence of episodes of rational optimism. I find that banks opening new branches in an MSA also lower their denial rates on mortgage applications associated with properties in that MSA, suggesting that branching decisions may be a reliable proxy for bank beliefs. Moreover, I find that banks reacting to positive changes in home prices or borrower incomes by more rapidly expanding their branch network also approve more mortgage applications, lending empirical evidence to episodes of rational optimism in the mortgage market.

CHAPTER 2

LAX LENDING STANDARDS, PRUDENTIAL POLICIES AND COMPETITION IN MORTGAGE MARKETS

2.1 INTRODUCTION

The size of the recent financial crisis has focused regulators' attention on developing macroprudential policies that will prevent and attenuate future episodes of financial instability. Lax lending standards are often cited as one of the causes of the recent crisis (see for example Acharya and Richardson 2009, Allen and Carletti 2009, Rajan 2010 or Taylor 2009). Additionally, there is a debate in the literature regarding the role of competition in financial stability (see for example Beck et al. 2013 or Freixas and Ma 2013). This chapter addresses these topics by studying two frictions that generate lax lending standards, including one which is related to competition, and policy tools to alleviate them.

The chapter has two parts. In the first part, I develop a quantitative model that incorporates the two frictions I study: 1) banks' limited liability and 2) banks failing to internalize that their behavior worsens the quality of the pool of borrowers faced by other lenders, which is more pronounced in competitive lending environments. I show that both frictions lead banks to devote too many resources to attracting borrowers

relative to screening them. That is, banks give too much low quality credit and "over-lend". I then study three policy tools to address the frictions: capital requirements, taxes on banks' lending and taxes on banks' borrowings.¹

In the second part of the chapter, I use a new database that I construct by merging Home Mortgage Disclosure Act (HMDA) data with data on the branch locations of commercial banks and savings institutions from the Federal Deposit Insurance Corporation's (FDIC) Summary of Deposits Survey. I run a panel data analysis of the effects of competition on the U.S. housing market at the Metropolitan Statistical Area (MSA) level. When competition is measured by a Herfindahl-Hirschman Index (HHI) based upon branch market shares, I find support for the model's implication that competition has a negative effect on lending standards. In addition, I find that this effect is stronger in markets that have an inelastic housing supply.

The first friction I consider, limited liability, has been widely recognized as a possible cause of excessive risk taking (Sinn 2001 surveys the literature). Under limited liability, negative returns to bank owners are limited to the amount of paid-in capital and the probability distribution of income is truncated. The second friction has been recently theorized by Hachem (2012). Hachem shows that if three conditions are met, then in a competitive equilibrium banks spend too many resources on attracting borrowers and screen them too little (generating excessive low quality lending) relative to a social planner (or monopoly bank) that internalizes the friction. These conditions are: 1) individual banks do not internalize that their behavior worsens the quality of the pool of borrowers faced by other lenders, 2) there is a tradeoff between screening

¹A tax on bank lending is very similar to the rules imposed by several emerging economies that require banks to deposit reserves with the Central Bank for each loan granted, and those reserves are not remunerated (see Lim et al. 2011 for a survey). The foregone interest on those reserves is a tax on banks' lending.

and attracting borrowers (for example, the time employees spend in screening tasks could be used in sales tasks), and 3) lending relationships last several periods.

In the model, there are banks and firms. Banks are each endowed with capital and a fixed amount of resources (e.g. time or employees) that they can use to look for borrowers or screen them. To make loans, banks use their endowed capital and borrow on the interbank market subject to a capital requirement constraint. Firms need credit to produce and try to borrow as much as they can from the banks. A firm's output depends on its idiosyncratic productivity (which is constant over time) and an aggregate productivity shock (which fluctuates over time). Because firms' idiosyncratic productivity is private information, banks can only observe it with some positive probability if they spend resources on screening or wait until the loan matures.

Each period in the model has two stages, and in each stage banks make two decisions: 1) how many resources to allocate between attracting borrowers and screening them and 2) whether to give credit to a borrower when matched. The resource allocation decision involves a tradeoff between screening (which I will call lending standards) and attracting borrowers.^{2,3} If banks screen less, it is more likely that they will attract a borrower, but less likely that they will initially discover the idiosyncratic productivity of that borrower. Banks take into account their expectations about the state of

²Heider and Inderst (2012) provide support for modeling the screening cost as an opportunity cost. They document that prospecting for loans and screening loan applicants are the two main tasks of loan officers. Their model shows that banks that incentivize their employees to attract more borrowers must pay a cost in terms of gathering soft information potentially useful for screening purposes.

³This tradeoff is borrowed from Hachem (2012) in order to incorporate the lack of internalization friction. Hence, the distributions of borrowers and the structure of the banks' problem in this chapter are similar to that presented in Hachem (2012). The main differences incorporated in this chapter are bank capital and bank balance sheet structure, capital requirements, limited liability, aggregate productivity shocks, bank failures, a different bank-borrower contract and a two-period framework.

the economy (the aggregate shock), the quality of the borrowers' pool and their cost of funds when making their decisions. In the first stage, banks form their expectations about the borrowers' pool based on the initial distribution. However, banks may keep profitable lending relationships from the first stage into the second stage, so in the second stage the quality of the borrowers' pool will change.

Both of the frictions I study push for overlending and lax lending standards. Because of limited liability, the banker is apt to take on more risk and screen less than a case where she internalizes the potential for losses to her own creditors. As in Hachem (2012), perfectly competitive banks in the first stage do not internalize that by giving credit and retaining good borrowers, they lower the quality of the pool of borrowers in the second stage. Thus, they allocate excessive resources to sales (too little screening) relative to a planner or monopoly bank that internalizes the friction. That is, banks follow an "attract now, screen later" behavior and give too much uninformed credit. Overlending is undesirable because it overexposes the banks to unexpected shocks. After a positive productivity shock, individual banks make more profits than if the frictions were not present, but they lose more money when a negative shock hits. Thus, banks' capital is too volatile in an equilibrium with the frictions, which induces excessive volatility in output because loans are partially financed with bank capital.

I calibrate the model to match several average ratios of the U.S. banking system (return on equity, losses, capital to asset ratios, and loans carried over across periods). Then I simulate productivity shocks and check the ability of the model to generate the correlation between the quality and quantity of U.S. credit. In the data there is a strong comovement between the quantity of credit and the quality of credit (measured by delinquencies or banks' charge-offs), which I document in Section 2.5.1. Namely,

periods of rapid loan growth are followed by periods of higher delinquency rates.⁴ The model is quite successful at matching this pattern.

I also show that overlending changes with macroeconomic conditions and that decreasing lending standards should not be confused with "lax standards". It is socially optimal for lending standards to be lower when the banks' costs of external funding are low and on the positive side of the business cycle (when borrowers' productivity and GDP are growing). Shaffer and Hoover (2008) provide empirical evidence that supports these results. However, the problem is that the frictions push for an excessive reduction of the standards in those cases, generating overlending. Given that overlending changes with macroeconomic conditions, the policy tools to fight it should also change.

The three policy tools that I study counteract the frictions by affecting the benefits of lending. By making lending less profitable, banks have less incentive to match and thus more to screen. However, the tools operate differently. Taxes alter the profitability per unit of credit while the capital requirements do not. With taxes the banks may keep lending the same amount to the good borrowers and instead be more demanding in terms of to whom they borrow. With higher capital requirements the banks do not become more selective with the borrowers, they just reduce the loan sizes for any borrower. In this sense, taxes are akin to a scalpel whereas capital requirements are a more blunt policy tool. In quantitative terms, I find that the taxes are better tools than the capital requirements because they reduce credit less to the more productive agents of the economy.

I use panel data analysis to study whether the main implication I draw from the model's lack of internalization friction is supported in the data, namely whether

⁴This fact also holds for many other countries (for example, see Elekdag and Wu 2011, Igan and Pinheiro 2011 or Mendoza and Terrones 2008).

more competitive markets exhibit lower levels of borrower screening. To test this implication, I combine publicly-available data on U.S. mortgage loan applications from HMDA with data on the branch locations of commercial banks and savings institutions from the FDIC's Summary of Deposits Survey. My database covers 366 MSAs across the U.S. from 2005-2011.⁵ I use various demographic and economic controls in my analysis, including data on MSA population and per capita personal income from the Bureau of Economic Analysis and house price data from Freddie Mac. I also use data provided by Saiz (2010) on housing supply elasticity.

My regression specifications test whether the denial rate of mortgage applications is higher, representing more borrower screening and higher lending standards, in MSAs that are more concentrated, as measured by the Herfindahl-Hirschman Index (HHI) of lenders' branch market shares. This index is a measure of the amount of competition among lenders' physical branch locations and takes on values between 0 and 1. Larger values of the branch HHI indicate market concentration, or the presence of a few dominant lenders that operate the majority of branches in an MSA. Smaller values indicate more competition among lenders with no dominant players. The specifications also test whether the relationship between denial rates and the branch HHI changes over the business cycle or with housing supply elasticity.

My empirical results show that competition does lower lending standards in the mortgage market. Furthermore, this relationship is more pronounced in markets with a highly inelastic housing supply. These results are robust to alternate specifications. In addition, for the post-crisis period, I find evidence that the effect of market concentration on lending standards is stronger during business cycle expansions.

⁵Unfortunately, there is not a comparable dataset to examine U.S. commercial lending, to which the model is calibrated. Though there are some differences between commercial and mortgage lending, these factors would not alter the existence of or the effect of the lack of internalization friction in the model, depending on competition.

The rest of the chapter proceeds as follows. Section 2.2 discusses related work. Section 2.3 presents the model, and Section 2.4 introduces the value functions. Section 2.5 documents some facts about the quality and quantity of U.S. credit, calibrates the model and discusses its quantitative properties. Section 2.6 studies the frictions and the excessive volatility they generate. Section 2.7 discusses the three policy tools. Section 2.8 discusses the database I construct and presents the panel data analysis of competition in the U.S. mortgage market. Section 2.9 concludes. Appendix A describes the sources of the data and the numerical algorithm.

2.2 LITERATURE REVIEW

This chapter contributes to the literature on four dimensions. First, I contribute to the quantitative literature on macroprudential policy. The majority of this literature has so far focused on frictions that generate "overborrowing", that is, frictions that lead borrowers to borrow "too much". The lender side does not play an important role in these models. In fact it is common to work with small open economy frameworks in which lenders are unmodeled. See, for example, the work on pecuniary frictions by Benigno et al. (2011), Bianchi (2011), Bianchi and Mendoza (2011), Davila (2011) or Jeanne and Korinek (2010). Mendoza and Korinek (2013) provide an excellent survey. This chapter complements this literature by taking the opposite approach. I focus on frictions that operate via the lenders, thus "overlending", and in the model borrowers play a very passive role. De Nicolo et al. (2011), Martinez-Miera and Suarez (2012) and Van den Heuvel (2008) are other quantitative papers studying prudential regulations and frictions originating from banks. I differ in the frictions studied.

Second, I compare different frictions and different policy tools using the same model. With the exception of De Nicolo et al. (2011), the literature has analyzed either only capital regulation or taxation.⁶ De Nicolo et al. (2011) study the joint impact of capital, liquidity regulations and tax proposals in a very different model in which the banks engage in maturity transformation, there is no screening and the frictions come from deposit insurance and fire sales. They study corporate income and liability taxes and find them to be inefficient.

Third, I provide a quantitative contribution to the literature on taxation of financial institutions that so far has focused on qualitative models. See for example Jeanne and Korinek (2010) or Perotti and Suarez (2011). IMF (2010) surveys existing work and recent policy proposals.

Fourth, I contribute to the literature that addresses the relationship between bank competition and financial stability. This strand of literature has not found a consensus, either theoretically or empirically, regarding the effect of competition on banks' risk taking and financial stability. See Freixas and Ma (2013) or Beck et al. (2013) for a discussion of the literature and for potential rationalizations of the lack of consensus.

To my knowledge, there are three other papers that study the effect of lender competition on lending standards using HMDA data, including Antoniadou (2013), Dell'Ariccia et al. (2012), and Rosen (2011). Those three papers differ from this chapter in the dependent variables and measures of competition they use. For dependent variables, Antoniadou (2013) and Dell'Ariccia et al. (2012) use denial decisions at the individual application level and Rosen (2011) uses the loan-to-income ratio,

⁶For quantitative papers studying capital requirements, see for example Angeloni and Faia (2013), Christensen et al. (2011), Collard et al. (2012), Corbae and D'Erasmus (2012), Covas and Fujita (2010), De Walque et al. (2010), Dib (2010), Gerali et al. (2010), Iacoviello (2010), Martinez-Miera and Suarez (2012), Subramanian and Yang (2012) or Van den Heuvel (2008).

whereas I study denial rates aggregated to the MSA-level. The other papers find that increased market share and market concentration based upon mortgage applications received, mortgage loans granted, and the share of local versus non-local lending lead to lower lending standards, while I find that a increased market concentration as measured by branch locations leads to higher lending standards. Thus, the proxies used seem to matter for the result that is found, in line with the debate in the competition-stability literature. Additionally, there is not yet a literature that studies both mortgage market competition and house supply elasticity, but Anundsen and Heebøll (2013) have shown empirically that inelastic housing markets have a stronger financial accelerator mechanism, where housing prices and credit are mutually reinforcing. Glaeser et al. (2008) find that more elastic housing markets experience fewer and shorter housing bubbles, but that the welfare consequences of these bubbles may be higher due to overbuilding.

2.3 MODEL

There are banks and firms that must form lending agreements to finance the production of a single good. Each period is divided into two stages and each stage is divided in two substages. To generate time series, I repeat the multi-stage problem, connecting the periods by the laws of motion for banks' capital and aggregate productivity.

2.3.1 FIRMS

There is a continuum of mass one of risk neutral firms. Firms are heterogeneous in idiosyncratic productivity (ω), which is uniformly distributed on the $[0, 1]$ interval.⁷ They have no storage technology and no endowment, so they must borrow from banks in order to produce. Their production technology is

$$y(\omega, z_t, L_t) = \theta \omega^\alpha z_t L_t \quad (2.1)$$

where θ and α are parameters, L_t is the size of the loan that the firm receives (unfinanced firms produce zero output), and z_t is an aggregate productivity shock that I model as a log-normal AR(1) process:

$$\log z_t = \rho_z \log z_{t-1} + \varepsilon_{z,t} \quad (2.2)$$

$$\varepsilon_{z,t} \sim N [0, \sigma_z^2] \quad (2.3)$$

I make a few simplifying assumptions. First, I assume that $y(\omega, z_t, L_t)$ is perfectly observable once the productivity shock is realized and that banks charge interest rates contingent on the observed output as if they were private equity investors. Several authors have previously used the simplification of banks as equity holders, for example Gertler and Karadi (2011). Here I use parameter $\kappa \geq 0$ to split output, $y(\omega, z_t, L_t)$, between the bank and the firm, with the bank receiving $(1 - \kappa)y(\omega, z_t, L_t)$ and the firm keeping $\kappa y(\omega, z_t, L_t)$. Thus, $(1 - \kappa)y(\omega, z_t, L_t)$ is the gross interest rate that a bank charges to a borrower of type ω who received a loan of size L_t . This assumption implies that my focus will be the quantity of credit instead of the price of credit. Third, to ensure that all firms seek the maximum financing, I assume that the firm's fraction κ cannot be seized by the banks for loan repayment. That is, from the firm's

⁷This is a simplifying assumption without loss of generality. Assuming a limited support for ω is the same as assuming that the set of investment opportunities of the bank is in fixed supply. This would happen if the number of interesting projects is finite.

side it is always optimal to apply for the maximum amount of credit available because the firm will always receive share κ of the surplus.

2.3.2 BANKS AND TIMING OF THE MODEL

At the start of each period t there is a continuum of mass one of risk neutral banks each endowed with bank capital K_t . Banks' capital remains fixed at K_t until the end of the period and evolves across periods as discussed in Section 2.3.5.⁸ Since I abstract from strategic interactions between banks and all banks are alike, I can think of this continuum as one bank which represents the aggregate banking system.

Each period is composed of two stages, denoted by 1 and 2, and in each stage an aggregate shock arrives. I divide each stage into two substages that I denote a) and b). In substages a) banks decide how to allocate resources between attracting customers and screening them. In substages b) banks decide whether to give credit to a borrower when matched.

Banks' decisions are made before the aggregate shock is realized in each stage, thus the bank always faces uncertainty about the business cycle. This means that if banks expect the aggregate shock to be high they can qualify a lower idiosyncratic productivity firm for financing. Banks must also take into account the distributions of borrowers they face when making decisions. I will discuss the borrower distributions in the next subsection.

Figure 2.1 illustrates the timing of the problem. For expositional purposes I refer to the stages as 1a, 1b, 2a and 2b:

1a) In stage 1a, the bank has to allocate one unit of resources (for example employees) between attracting customers or screening them. If banks screen less,

⁸This assumption is without loss of generality because, as I show in Section 2.4, the value functions are linear in bank capital and the level of capital does not matter for the screening decision or for the decision to give credit.

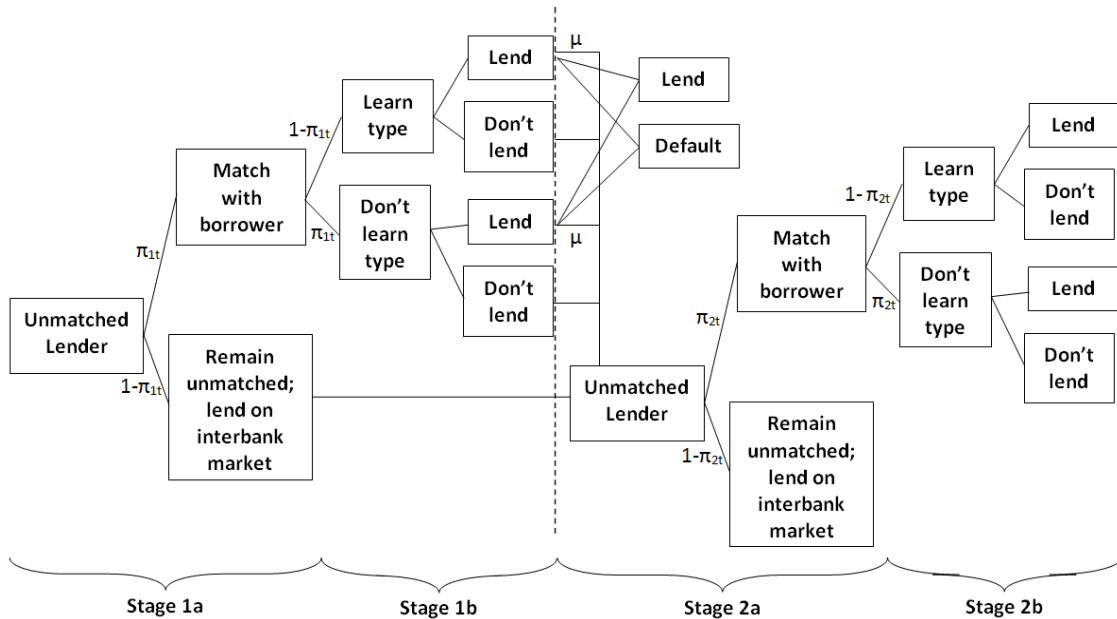


Figure 2.1: Summary of Bank's Problem in Period t .

it is more likely that the bank will meet a borrower, but less likely that the bank can initially discover the idiosyncratic productivity of the borrower. Thus, the cost of screening is an opportunity cost in terms of sales. This tradeoff between screening and sales activities comes from Hachem (2012), but the results of the model would also hold if alternatively I assume that the cost of screening is in terms of the numeraire and banks face a budget constraint. This tradeoff also captures the empirical fact that when banks want to rapidly increase their lending volumes they reallocate part of their resources from screening tasks to sales tasks. The no-documentation loans observed often during the last financial crisis is an extreme example of the "loan sales versus screening" trade-off as in those cases the loan originator only performed sales tasks.

I denote by π_{1t} the fraction of resources spent on trying to match with borrowers, and by $(1 - \pi_{1t})$ the fraction spent on screening. Thus I interpret π_{1t} as the probability of matching, and $(1 - \pi_{1t})$ as the probability of successfully discovering a borrower's type (ω). Banks may only match with one borrower at a time. The choice of π_{1t} depends on banks' beliefs about the quality of the borrower pool in the different stages of the game and on aggregate productivity. Once the bank decides π_{1t} , then it will: 1) become matched with a borrower and learn that borrower's type with probability $\pi_{1t}(1 - \pi_{1t})$, I call these bankers "informed"; 2) become matched with a borrower and not learn that borrower's type with probability π_{1t}^2 , I call these banks "uninformed"; or 3) remain unmatched with probability $(1 - \pi_{1t})$. If I interpret the continuum of banks as the aggregate banking system, then π_{1t}^2 will be the fraction of banks who may be giving credit without adequate screening.

1b) In stage 1b, banks that remained unmatched in stage 1a invest their capital (for example, in the international money markets) at rate i_b .⁹ Banks that successfully matched with a borrower must decide whether to lend to their borrower. The decision about whether to give credit depends on the bank's information about its borrower's idiosyncratic productivity and on expectations about both the state of the economy (the aggregate shock) and the quality of the borrowers' pool. Banks who do not give credit can invest their capital in the money markets at the rate i_b . Thus i_b is the opportunity cost for the bank of lending to a firm, and it puts a floor on the return the banks require from borrowers in order to lend to them. I assume i_b to be exogenous for simplicity. This is a common assumption used in macroprudential models such as Bianchi (2011) or Bianchi and Mendoza (2011). Boz and Mendoza (2013) provide an empirical justification, noting that the banking system is only one of the players in

⁹For simplicity, I abstract from modeling risk in the money markets in order to focus on banks' credit decisions. Since banks are risk neutral, it does not matter if I assume that this return is safe or risky. Risk neutral banks make decisions based on expected values.

the money markets and even the U.S. risk-free rate has been significantly influenced by outside factors.

To finance a loan, banks can use their own capital and they can borrow B_t at the rate i_b .¹⁰ Banks are subject to a capital requirement, $\gamma \geq 0$, such that

$$L_t = B_t + K_t \quad (2.4)$$

$$K_t \geq \gamma L_t \quad (2.5)$$

At the end of stage 1b, the aggregate productivity shock is realized and all banks discover their borrower's type. Banks who gave credit either make enough profits to repay outside funding, or they did not and have to default. To track which banks make positive profits and which ones make losses and default, I use the following indicator function that takes the value one when a bank is profitable in stage 1

$$\Omega_1(\omega, z_1) = \begin{cases} 0 & \text{if } (1 - \kappa)y(\omega, z_1, L_t) \leq (1 + i_b)B_t \\ 1 & \text{if } (1 - \kappa)y(\omega, z_1, L_t) > (1 + i_b)B_t \end{cases} \quad (2.6)$$

where $(1 - \kappa)y(\omega, z_1, L_t)$ is the revenue from a borrower of type ω after the productivity shock of stage 1b. Banks that do not default hold on to their profits and again use capital, K_t , in the second stage.¹¹ Defaulting banks disappear and their borrowers are returned to the pool of unmatched borrowers. Thus at stage 2a the mass of banks will be smaller than one, and aggregate capital available for lending is smaller than K_t .

2a) At the start of stage 2a, profitable banks can decide to keep their borrowers from stage 1 by lending to them. However, there is an exogenous separation shock

¹⁰Assuming a borrowing rate below the money market rates would not affect the results of the model since the capital requirement limits the ability of the banks to exploit the arbitrage opportunity.

¹¹Any stage 1b profits or losses are integrated into the aggregate capital stock at the end of the period, as described in Section 2.3.5.

that happens with probability μ and destroys the lending relationship. Banks hit by the shock return to the pool of available banks and their borrowers return to the pool of available borrowers. The role of this shock is to improve the quality of the borrower pool in the second stage. An alternative and equivalent specification would be to assume a new flow of borrowers after stage 1b.

In stage 2a banks unmatched from before and those that separated decide the fraction of resources (π_{2t}) to spend on matching with borrowers. The decision depends on banks' beliefs about the quality of the borrower distribution in stage 2a and about the aggregate shock. As I describe in Section 2.3.4, the beliefs about the distribution depend on the amount of lending that took place in the first stage.

2b) In stage 2b banks who are matched with a borrower can be informed or uninformed and must decide whether to extend credit to their borrower (as in stage 1b). Uninformed banks' decisions must take into account that the quality of the pool of available borrowers is different than in Stage 1b, so their expectation of the borrower type they met has changed. At the end of stage 2b, the second productivity shock is realized, the period is over and all banks are separated from borrowers. To avoid keeping track of each individual bank's capital, I assume that profits or losses are integrated into the aggregate capital stock and that this is equally distributed among the continuum of banks. Section 2.3.5 describes the law of motion for bank capital. New banks enter so that I again have mass one of banks when a new period starts.

I simulate the model as a sequence of periods, each involving the four steps described above. Periods are connected because the amount of capital (K_t) changes between periods as discussed in Section 2.3.5, and because any aggregate productivity shock depends on the previous one. Thus, there are two sources of endogenous

volatility in the economy: changes in lending standards and changes in bank capital over periods.

To dampen the volatility of screening intensity in time series simulations, I introduce an adjustment cost $\frac{c}{2} (\pi_{it} - \pi^{ss})^2 K_t$, $i = 1, 2$, which is commonplace in macro models. I model the adjustment cost to be proportional to the bank capital stock because this stock grows over time and otherwise the adjustment cost would disappear.¹²

To simplify the notation in the rest of the model exposition, for variables that do not relate to different periods I will drop the t subscript. Thus, instead of using the π_{1t} notation to denote stage 1 of period t , I will just write π_1 . It is important to note that with this notation I do not mean that all periods are alike. That is, I am not assuming $\pi_{1t} = \pi_1 \forall t$. Since K_t does not change across the stages of period t , I will keep the K_t notation to emphasize that it only changes across periods and it is not a constant. For productivity, given the AR(1) nature of the process, banks take into account the last value of the productivity shock before they take decisions at t . I denote by z_{-1} the last shock that occurred in period $t - 1$, by z_1 the first shock of period t and by z_2 the second shock of period t .

2.3.3 BANKS' DECISIONS

For risk neutral banks it is optimal either to lend nothing, or to lend as much as allowed by the capital requirement by borrowing on the money markets:

$$L_t = \frac{K_t}{\gamma} \tag{2.7}$$

$$B_t = \left(\frac{1}{\gamma} - 1 \right) K_t \tag{2.8}$$

¹²Although the capital stock grows over time, it does not affect banks' resource allocation or credit decisions because the banks' value functions are linear in bank capital. The banks' value functions are presented in Section 2.4.

That is, the capital requirement constraint is only binding for banks matched with a borrower expected to be profitable. Since not all banks are in that situation, the model can match the empirical fact documented by Allen et al. (2011) among others that for U.S. commercial banks the average capital-to-asset ratio is twice the 4% that capital regulation dictated. Aiyar et al. (2012), Alfon et al. (2005) and Francis and Osborne (2009) show that even if most banks keep more capital than the regulatory minimum, the extra buffer is constant over time and capital requirements do affect the actual capital-to-asset ratios. Thus, in the data, even if the constraint is not literally binding, banks change their capital level as the regulatory minimum changes as if the constraint was binding.

Informed and uninformed banks have different information with which to make the decision of whether to lend to a borrower. Informed banks know the idiosyncratic productivity of their borrower and take expectations over aggregate productivity in each stage to compute the expected revenue from lending L_t to borrower of type ω . In the first stage, expected revenues from borrower ω are

$$R_1(\omega, z_{-1}, L_t) \equiv \int_0^{\infty} (1 - \kappa)y(\omega, z_1, L_t)f(z_1|z_{-1})dz_1 \quad (2.9)$$

where the conditional density is $f(z_1|z_{-1})$, reflecting that the expectation in the first stage is a function of past productivity, z_{-1} .

An informed bank in stage 1b will lend if her expected earnings from lending to borrower ω after repaying the bank's borrowings, $R_1(\omega, z_{-1}, L_t) - (1+i_b)B_t$, is greater than the opportunity cost of the bank capital lent, that is the return of investing at rate i_b in the money markets, $(1+i_b)K_t$. I define the pivotal borrower in stage 1 as $\bar{\omega}_1$, that is, the bank will lend to any type ω better than or equal to $\bar{\omega}_1$

$$R_1(\bar{\omega}_1, z_{-1}, L_t) = (1+i_b)(B_t + K_t) \quad (2.10)$$

To keep track of informed banks lending, I define an indicator function that takes the value one for informed banks matched with borrowers worthy of credit:

$$A_1(\omega, z_{-1}) = \begin{cases} 0 & \text{if } \omega < \bar{\omega}_1 \\ 1 & \text{if } \omega \geq \bar{\omega}_1 \end{cases} \quad (2.11)$$

Similarly, in stage 2 the pivotal borrower for an informed bank, $\bar{\omega}_2$, is the type ω satisfying

$$R_2(\bar{\omega}_2, z_1, L_t) = (1 + i_b)(B_t + K_t) \quad (2.12)$$

where

$$R_2(\omega_2, z_1, L_t) \equiv \int_0^{\infty} (1 - \kappa)y(\omega_2, z_2, L_t)f(z_2|z_1)dz_2 \quad (2.13)$$

where $f(z_2|z_1)$ represents the density with respect to the aggregate shock in the second stage. I define again an indicator function to keep track of informed banks lending in stage 2:

$$A_2(\omega, z_1) = \begin{cases} 0 & \text{if } \omega < \bar{\omega}_2 \\ 1 & \text{if } \omega \geq \bar{\omega}_2 \end{cases} \quad (2.14)$$

Uninformed banks do not know their borrower's type, so they need to take expectations over both aggregate productivity and the borrower type they will meet. The banks' expected density function of available borrowers of type ω in stage 1a, $\psi_1(\omega)$, which I define in the next subsection, is then central to the expected return from uninformed lending. The expected revenue from uninformed lending in the first stage is

$$R_1^U(\psi_1(\cdot), z_{-1}, L_t) \equiv \int_0^1 \int_0^{\infty} (1 - \kappa)y(\omega, z_1, L_t)f(z_1|z_{-1})\psi_1(\omega)d\omega dz_1 \quad (2.15)$$

Like the informed bank, for an uninformed bank, the opportunity cost of lending is the return from investing its capital in the money markets, $(1 + i_b)K_t$. Uninformed banks lend if they expect revenue $R_1^U(\psi_1(\cdot), z_{-1}, L_t)$ minus the bank's borrowing

costs to be greater than or equal to the opportunity cost of lending. I keep track of uninformed banks lending using the following indicator function:

$$A_1^U(\psi_1(\cdot), z_{-1}) = \begin{cases} 0 & \text{if } R_1^U(\psi_1(\cdot), z_{-1}, L_t) < (1 + i_b)(B_t + K_t) \\ 1 & \text{if } R_1^U(\psi_1(\cdot), z_{-1}, L_t) \geq (1 + i_b)(B_t + K_t) \end{cases} \quad (2.16)$$

where the decision to lend or not by uninformed banks is a function of aggregate productivity and the distribution of idiosyncratic productivity in the pool of available borrowers.

Similarly, if $\psi_2(\omega)$ is the density function of available borrowers of type ω in stage 2a (I define it in the next subsection), then the expected revenue from uninformed lending in stage 2 is

$$R_2^U(\psi_2(\cdot), z_1, L_t) \equiv \int_0^1 \int_0^\infty (1 - \kappa)y(\omega, z_2, L_t)f(z_2|z_1)\psi_2(\omega)dz_2d\omega \quad (2.17)$$

Uninformed banks will lend in stage 2 if the following indicator function takes the value one:

$$A_2^U(\psi_2(\cdot), z_1) = \begin{cases} 0 & \text{if } R_2^U(\psi_2(\cdot), z_1, L_t) < (1 + i_b)(B_t + K_t) \\ 1 & \text{if } R_2^U(\psi_2(\cdot), z_1, L_t) \geq (1 + i_b)(B_t + K_t) \end{cases} \quad (2.18)$$

Again, the decision to lend or not by uninformed banks is a function of aggregate productivity and the distribution of idiosyncratic productivity in the pool of available borrowers in stage 2 ($\psi_2(\cdot)$).

Combining equations (2.7) and (2.8) with the decision rules discussed above, I can show that the bank's choice of whether or not to lend does not depend on the amount of bank capital. The capital requirement (γ) does not affect the pivotal borrower, but it plays a role in the choice of how much to screen because it determines the fraction of each loan the bank finances with its own money ("the skin in the game") and because it affects the size of a loan.

2.3.4 THE DISTRIBUTIONS OF BORROWERS

The quality and size of the pool of available borrowers depends on the actions of all banks, and thus on aggregate lending intensity, Π . In Section 2.3.6 I relate aggregate lending intensity to individual banks' lending intensity and banks' expectations.

All borrowers begin the first stage unmatched, thus the banks' beliefs about the probability of type ω being in the pool of available borrowers, $\psi_1(\omega)$, is the initial uniform distribution on the unit interval

$$\psi_1(\omega) = 1. \tag{2.19}$$

After stage 1a there is a distribution of matched borrowers with informed financing, $\lambda_1(\omega)$, and a distribution of matched borrowers with uninformed financing, $\phi_1(\omega)$. Because all banks and borrowers begin stage 1a unmatched, the probability of a borrower of type ω receiving informed financing in stage 1a is:

$$\lambda_1(\omega) = \Pi_1(1 - \Pi_1)A_1(\omega, z_{-1}) \tag{2.20}$$

where $\Pi_1(1 - \Pi_1)$ is the probability of a match in stage 1a with an informed bank, and the function $A_1(\omega, z_{-1})$ captures whether the bank gives credit to that type ω .

The probability of a borrower of type ω receiving uninformed financing in stage 1a is:

$$\phi_1(\omega) = \Pi_1^2 A_1^U(\psi_1(\cdot), z_{-1}) \tag{2.21}$$

where Π_1^2 is the probability of a first period match with an uninformed bank and $A_1^U(\psi_1(\cdot), z_{-1})$ captures if the uninformed lender chooses to lend.

In stage 2a, banks update their beliefs because they know that the pool of available borrowers has changed. The probability of meeting type ω in the pool of available

borrowers in the second stage is

$$\psi_2(\omega) = \frac{1 - A_2(\omega, z_1)\Omega_1(\omega, z_1)(1 - \mu)(\lambda_1(\omega) + \phi_1(\omega))}{\int_0^1 [1 - A_2(\omega, z_1)\Omega_1(\omega, z_1)(1 - \mu)(\lambda_1(\omega) + \phi_1(\omega))] d\omega}. \quad (2.22)$$

The first term of the numerator accounts for the fact that type ω begins stage 1 unmatched. The second term of the numerator takes into account the probability a lender match with type ω is carried over into stage 2a. In order for a match to be carried over, type ω must have been 1) matched and lent to in stage 1, $\lambda_1(\omega) + \phi_1(\omega)$; 2) not hit by a separation shock with probability μ , $1 - \mu$; 3) profitable enough for the bank to not have defaulted, $\Omega_1(\omega, z_1) = 1$; and 4) profitable enough that the bank will lend again in stage 2, $A_2(\omega, z_1) = 1$. Thus, the numerator is the probability that type ω is in the pool of available borrowers at stage 2a. The denominator sums over all available borrowers.

In addition to the characteristics of the pool of available borrowers, given that banks can only match with one borrower, I must keep track of the size of the pool of unmatched banks. The size of the pool of unmatched banks in stage 2a is η_2

$$\eta_2 = 1 - \int_0^1 [(1 - \Omega_1(\omega, z_1)) + A_2(\omega, z_1)\Omega_1(\omega, z_1)(1 - \mu)] (\lambda_1(\omega) + \phi_1(\omega)) d\omega \quad (2.23)$$

where the first term accounts for the initial mass of banks and the integral term accounts for the mass of banks that are not in the pool of unmatched banks in stage 2a. The integral contains a weighting term, $\lambda_1(\omega) + \phi_1(\omega)$, which captures the probability that a bank matches with and finances a type ω , and a term that captures the two reasons why a bank may not be in the pool of unmatched banks in the second stage: a) because the bank matched, gave credit and made negative profits, $\Omega_1(\omega, z_1) = 0$; or b) because the bank matched and made profits, $\Omega_1(\omega, z_1) = 1$, was not hit by the separation shock and decided to keep its borrower, $A_2(\omega, z_1) = 1$.

The amount of available banks and borrowers affects the number of matches formed in the second stage. Thus, for example, the amount of new informed matches at the end of stage 2a will be $\psi_2(\omega)\eta_2\Pi_2(1 - \Pi_2)$.

Following the same reasoning as before, in stage 2b the borrowers' distributions are:

- 1) The probability of a borrower of type ω receiving informed financing in stage 2a:

$$\lambda_2(\omega) = A_2(\omega, z_1)(1 - \mu)\Omega_1(\omega, z_1)(\lambda_1(\omega) + \phi_1(\omega)) + \psi_2(\omega)\eta_2\Pi_2(1 - \Pi_2)A_2(\omega, z_1) \quad (2.24)$$

where the first term is the fraction of profitable borrowers financed in stage 1b, $\Omega_1(\omega, z_1)(\lambda_1(\omega) + \phi_1(\omega))$, who were not hit by the separation shock, $(1 - \mu)$, and were rolled-over, $A_2(\omega, z_1) = 1$. I am assuming that all banks learn about their borrower's type once each loans mature thus uninformed matches became informed, as the term $\phi_1(\omega)$ accounts for. The second term in (2.24) is the fraction of unmatched borrowers, $\psi_2(\omega)$, that with probability $\Pi_2(1 - \Pi_2)$ formed an informed match with one of the η_2 available banks giving credit to that borrower type, $A_2(\omega, z_1) = 1$.

- 2) The probability of a borrower of type ω receiving uninformed financing in stage 2a is:

$$\phi_2(\omega) = \psi_2(\omega)\eta_2\Pi_2^2 A_2^U(\psi_2(\cdot), z_1) \quad (2.25)$$

where $\psi_2(\omega)$ represents the fraction of available borrowers, and this is multiplied by the probability that these unmatched borrowers meet an uninformed bank, $\eta_2\Pi_2^2$, giving credit, $A_2^U(\psi_2(\cdot), z_1) = 1$.

2.3.5 PROFITS OF THE BANKING SECTOR

I assume that banks pay no dividends and capital evolves as retained earnings. The aggregate capital at the end of period t , that is, the capital available for the new bank cohort which starts at $t + 1$, is the sum across both stages of the profits/losses of the informed and uninformed banks, plus the profits of the unmatched lenders:

$$K_{t+1} = K_{t+1}^1 + K_{t+1}^2 \quad (2.26)$$

where I denote by K_{t+1}^1 the contribution to next period's capital from stage one:

$$K_{t+1}^1 = \int_0^1 \left\{ \begin{aligned} & (\max \{0, (1 - \kappa)y(\omega, z_1, L_t) - (1 + i_b)B_t\}) [\lambda_1(\omega) + \phi_1(\omega)] + \\ & + (1 + i_b) K_t (1 - \lambda_1(\omega) - \phi_1(\omega)) - \frac{c}{2} (\pi_1 - \pi_1^{ss})^2 K_t \end{aligned} \right\} d\omega \quad (2.27)$$

The amount of banks lending is $\lambda_1(\omega) + \phi_1(\omega)$, thus $(1 - \lambda_1(\omega) - \phi_1(\omega))$ are investing in the money markets.¹³ Among those banks lending, limited liability means that the banks' maximum loss is their capital. This is captured by the *max* operator, which ensures that banks' revenue minus banks' borrowings is never negative.

The contribution to next period's capital from stage two is

$$K_{t+1}^2 = \int_0^1 \left\{ \begin{aligned} & (\max \{0, (1 - \kappa)y(\omega, z_2, L_t) - (1 + i_b)B_t\}) [\lambda_2(\omega) + \phi_2(\omega)] + \\ & + (1 + i_b) K_t \eta_2 [1 - \psi_2(\omega) \Pi_2 [\Pi_2 A_2^U(\psi_2(\cdot), z_1) + (1 - \Pi_2) A_2(\omega, z_1)]] + \\ & - \eta_2 \left[\frac{c}{2} (\pi_2 - \pi_2^{ss})^2 K_t \right] \end{aligned} \right\} d\omega \quad (2.28)$$

where $\lambda_2(\omega) + \phi_2(\omega)$ are the banks lending in stage 2. The term

$$\eta_2 [1 - \psi_2(\omega) \Pi_2 [\Pi_2 A_2^U(\psi_2(\cdot), z_1) + (1 - \Pi_2) A_2(\omega, z_1)]]$$

represents unmatched banks at the start of the second stage, η_2 , that did not become uninformed lenders giving credit, $\psi_2(\omega) \eta_2 \Pi_2^2 A_2^U(\psi_2(\cdot), z_1)$, nor became informed

¹³As discussed earlier, any profits or losses from stage 1 are incorporated into the aggregate capital stock at the end of the period. I abstract from modeling risk in money market returns in order to focus on banks' credit decisions.

lenders giving credit, $\psi_2(\omega)\eta_2\Pi_2(1 - \Pi_2)A_2(\omega, z_1)$, thus they are unmatched and invest in money markets.

2.3.6 EQUILIBRIUM

I look for equilibria that satisfy the symmetry condition that individual bank lending intensity is consistent across the aggregate banking system:

$$\Pi_{it} = \pi_{it} \quad \forall t, i = 1, 2 \tag{2.29}$$

I will compare two cases. In the first case, I consider monopoly banks. Monopoly banks internalize that their behavior affects the quality of the pool of borrowers they will face tomorrow. That is, monopoly bankers incorporate (2.29) into their decision problem. Thus, there is no friction as monopoly banks correctly internalize that their choice of lending intensity π alters Π . In the second case, perfectly competitive banks do not internalize the effect of their choice of π on Π , for example because they are small, face a high degree of competition and think their actions are not significant enough to affect the quality of the borrower's pool. In equilibrium (2.29) holds, but since banks do not integrate (2.29) into their decision problem the friction is at its maximum.

I define an equilibrium in the model when, for exogenous cost of funds i_b and productivity z that evolves according to (2.2) and (2.3), firms and banks optimize and (2.29) holds. The next section describes the value functions and Appendix A.2 details the numerical algorithm. The problem of a firm is trivial: always look for the maximum possible credit because output is increasing in credit and the firm can always keep fraction κ of output. Bankers' problem is to maximize profits in each period t and stages $i = 1, 2$, by choosing π_i , $A_i(\omega, z_{i-1})$, $A_i^U(\psi_i(\cdot), z_{i-1})$, and L_i , subject to borrower distributions, to the two possible cases for beliefs on the effect of

π on Π , to banks' balance sheet equality (2.4) and to the capital requirement (2.5). Given the capital inherited from the previous period, the capital for the following period will be determined according to equations (2.26) – (2.28).

2.4 BANK'S VALUE FUNCTIONS

A bank can be in 3 different situations: 1) unmatched with a borrower, in which case I denote the value function by U ; 2) matched with a borrower knowing the borrower's type, with value function J ; or 3) matched with a borrower without knowing the borrower's type, with value function N . All value functions are linear functions of the initial level of bank capital. The value functions also depend on the aggregate productivity level. For informed banks the value function depends on the type ω , and for unmatched and uninformed banks it depends on the distribution of idiosyncratic productivity of available borrowers.

The value functions presented below incorporate both of the frictions I study in this chapter. Limited liability is present, since bank lending revenues are subject to a *max* operator, $\max\{0, (1 - \kappa)y(\omega, z_i, L_t) - (1 + i_b)B_t\}$ for $i = 1, 2$, that ensures banks' maximum loss is their own capital. The lack of internalization friction is present because banks do not incorporate equation (2.29) in their decision problem. I can eliminate limited liability from the banks' problem by removing the *max* operator and allowing banks to incur losses above their capital. Likewise, I can eliminate the lack of internalization friction by imposing that banks incorporate equation (2.29).¹⁴

¹⁴I conduct a comparative statics exercise in Section 2.6.1 that examines the level of screening generated by each friction separately and by the model without either friction.

2.4.1 UNMATCHED BANK

The value function of an unmatched bank in stage 1a is

$$\begin{aligned}
U_1(\psi_1(\cdot), K_t, z_{-1}) = & \max_{0 \leq \pi_1 \leq 1} \left\{ \pi_1^2 N_1(\psi_1(\cdot), K_t, z_{-1}) + \pi_1(1 - \pi_1) \int_0^1 J_1(\omega, K_t, z_{-1}) \psi_1(\omega) d\omega + \right. \\
& \left. + (1 - \pi_1) [(1 + i_b) K_t + E_1(U_2(\psi_2(\cdot), K_t, z_1))] - \frac{c}{2} (\pi_1 - \pi_1^{ss})^2 K_t \right\}
\end{aligned} \tag{2.30}$$

with the expectation

$$E_1(U_2(\psi_2(\cdot), K_t, z_1)) = \int_0^\infty U_2(\psi_2(\cdot), K_t, z_1) f(z_2 | z_{-1}) dz_2 \tag{2.31}$$

The first term of (2.30) is the probability of forming an uninformed match, π_1^2 , times the value of an uninformed match, $N_1(\psi_1(\cdot), K_t, z_{-1})$. The second term is the probability of forming an informed match, $\pi_1(1 - \pi_1)$, times the expected value of such a match, where the expectation is taken with respect to the borrower type. The third term is the probability of remaining unmatched, $(1 - \pi_1)$, times the value of being unmatched (the return from lending at rate i_b plus the expected value of being unmatched in the second stage). The last term is the adjustment cost. In stage 1a unmatched banks optimize over π_1 .

Similarly, in stage 2a unmatched banks optimize over π_2 . Their value function is:

$$\begin{aligned}
U_2(\psi_2(\cdot), K_t, z_1) = & \max_{0 \leq \pi_2 \leq 1} \left\{ \pi_2^2 N_2(\psi_2(\cdot), K_t, z_1) + \right. \\
& \left. + \pi_2(1 - \pi_2) \int_0^1 J_2(\omega, K_t, z_1) \psi_2(\omega) d\omega + \right. \\
& \left. + (1 - \pi_2) (1 + i_b) K_t - \frac{c}{2} (\pi_2 - \pi_2^{ss})^2 K_t \right\}.
\end{aligned} \tag{2.32}$$

This function is similar to equation (2.30) with the difference banks know that their cohort dies at the end of the second stage.

2.4.2 MATCHED BANK KNOWING BORROWER'S TYPE

The value function of a matched informed bank in stage 1b is the maximum between lending to her borrower, $A_1(\cdot) = 1$, or not lending:

$$\begin{aligned}
 J_1(\omega, K_t, z_{-1}) = & \max_{A_1(\omega, z_{-1}) \in \{0,1\}} \left\{ (1 - A_1(\omega, z_{-1})) [(1 + i_b) K_t + E_1(U_2(\psi_2(\cdot), K_t, z_1))] + \right. \\
 & \left. + A_1(\omega, z_{-1}) \left[\int_0^\infty (\max \{0, (1 - \kappa)y(\omega, z_1, L_t) - (1 + i_b)B_t\}) f(z_1|z_{-1}) dz_1 + \right. \right. \\
 & \left. \left. + \int_0^\infty \Omega_1(\omega, z_1) \begin{pmatrix} \mu E_1[U_2(\psi_2(\cdot), K_t, z_1)] \\ +(1 - \mu)E_1[J_2(\omega, K_t, z_1)] \end{pmatrix} f(z_1|z_{-1}) dz_1 \right] \right\}
 \end{aligned} \tag{2.33}$$

where the first term accounts for the bank not lending, investing in the money market and being unmatched in stage 2. The second term accounts for the bank lending to a borrower, $A_1(\cdot) = 1$. This bank receives revenue $(1 - \kappa)y(\omega, z_1, L_t)$ and repays borrowings up to the limited liability constraint, that is, its maximum loss is the amount of bank capital. If the bank made profits, $\Omega_1(\omega, z_1) = 1$, next stage the informed bank can keep its borrower (if not hit by a separation shock) and reevaluate if it wants to lend or not. The financing decision is made before the productivity shock z_1 is known. The expectations $E_1[U_2(\cdot)]$ and $E_1[J_2(\cdot)]$ are taken over future productivity shocks as in (2.31).

By the same reasoning, the value of an informed match in stage 2b is

$$\begin{aligned}
 J_2(\omega, K_t, z_1) = & \max_{A_2(\omega, z_1) \in \{0,1\}} \left\{ (1 - A_2(\omega, z_1)) (1 + i_b) K_t + \right. \\
 & \left. + A_2(\omega, z_1) \left[\int_0^\infty (\max \{0, (1 - \kappa)y(\omega, z_2, L_t) - (1 + i_b)B_t\}) f(z_2|z_1) dz_2 \right] \right\}
 \end{aligned} \tag{2.34}$$

where the difference relative to (2.33) is that banks know that their cohort dies at the end of the second stage.

2.4.3 MATCHED BANK WHO DOES NOT KNOW BORROWER'S TYPE

The value function of a matched uninformed bank in the first stage is the maximum between lending without knowing her borrower's type, $A_1^U(\psi_1(\cdot), z_{-1}) = 1$, or not lending:

$$\begin{aligned}
 N_1(\psi_1(\cdot), K^t, z_{-1}) &= \max_{A_1^U(\psi_1(\cdot), z_{-1}) \in \{0,1\}} \{ (1 - A_1^U(\psi_1(\cdot), z_{-1})) [(1 + i_b) K_t + E_1[U_2(\psi_2(\cdot), K_t, z_1)]] + \\
 &+ A_1^U(\psi_1(\cdot), z_{-1}) \left[\int_0^1 \int_0^\infty (\max \{0, (1 - \kappa)y(\omega, z_1, L_t) - (1 + i_b)B_t\}) f(z_1|z_{-1})\psi_1(\omega) dz_1 d\omega + \right. \\
 &\left. + \int_0^1 \int_0^\infty \Omega_1(\omega, z_1) \begin{pmatrix} \mu E_1[U_2(\psi_2(\cdot), K_t, z_1)] \\ +(1 - \mu)E_1[J_2(\omega, K_t, z_1)] \end{pmatrix} f(z_1|z_{-1})\psi_1(\omega) dz_1 d\omega \right] \} \\
 & \tag{2.35}
 \end{aligned}$$

where the first term accounts for the bank not lending, investing in the money market and being unmatched in stage 2. The second term accounts for the expected value from lending to a borrower. To compute expected profits the uninformed bank takes expectations over both productivity and the borrower's distribution. Limited liability limits the amount of the losses. If the bank made profits, $\Omega_1(\omega, z_1) = 1$, next stage the bank is informed and can keep its borrower (if not hit by a separation shock) and reevaluate if it wants to lend or not.

The value of an uninformed match in stage 2b is

$$\begin{aligned}
 N_2(\psi_2(\cdot), K_t, z_1) &= \max_{A_2^U(\psi_2(\cdot), z_1) \in \{0,1\}} \{ (1 - A_2^U(\psi_2(\cdot), z_1)) (1 + i_b) K_t + \\
 &+ A_2^U(\psi_2(\cdot), z_1) \left[\int_0^1 \int_0^\infty (\max \{0, (1 - \kappa)y(\omega, z_2, L_t) - (1 + i_b)B_t\}) f(z_2|z_1)\psi_2(\omega) dz_2 d\omega \right] \} \\
 & \tag{2.36}
 \end{aligned}$$

where the difference relative to (2.35) is that banks know that their cohort dies at the end of the second stage.

2.5 CALIBRATION AND QUANTITATIVE PROPERTIES OF THE MODEL

In this section, I document business cycle facts about the quality and quantity of bank credit in the U.S. Then I calibrate the model to match several average ratios of the U.S. banking system (return on equity, losses, capital to asset ratios, and loans carried over across periods), simulate productivity shocks and check the ability of the model to replicate the previous facts. I will use this calibrated model in the following sections of the chapter.

2.5.1 SOME FACTS ABOUT THE QUALITY AND QUANTITY OF CREDIT

To document business cycle facts about U.S. bank credit, I use annual data from 1987-2010. This is the longest period for which my variables of interest are available. I deflate nominal variables using the GDP deflator and detrend the data using an H-P filter.¹⁵ The sources for the data are listed in Appendix A.1.

Figure 2.2 illustrates the relationship between the quantity and quality of credit extended by U.S. commercial banks. Panel A plots the level of business credit to GDP along with two proxies for the quality of credit: the delinquency and charge-off rates on business loans. Both credit quality variables are strongly positively correlated and lag the quantity of credit.

Panel B plots the cyclical components of the quantity and quality of business credit against the industrial production cycle. Panel C reproduces Panel B but for aggregate measures of credit and plots GDP instead of industrial production. As documented by Lown et al. (2000) and others, bank credit is procyclical. That is, bank credit rises with industrial production and GDP during business cycle expansions and falls

¹⁵To detrend the series, I used an H-P filter with parameter set to 100, as is common in business cycle papers such as Backus and Kehoe (1992). The facts do not change if I use the 6.25 parameter proposed by Ravn and Uhlig (2002).

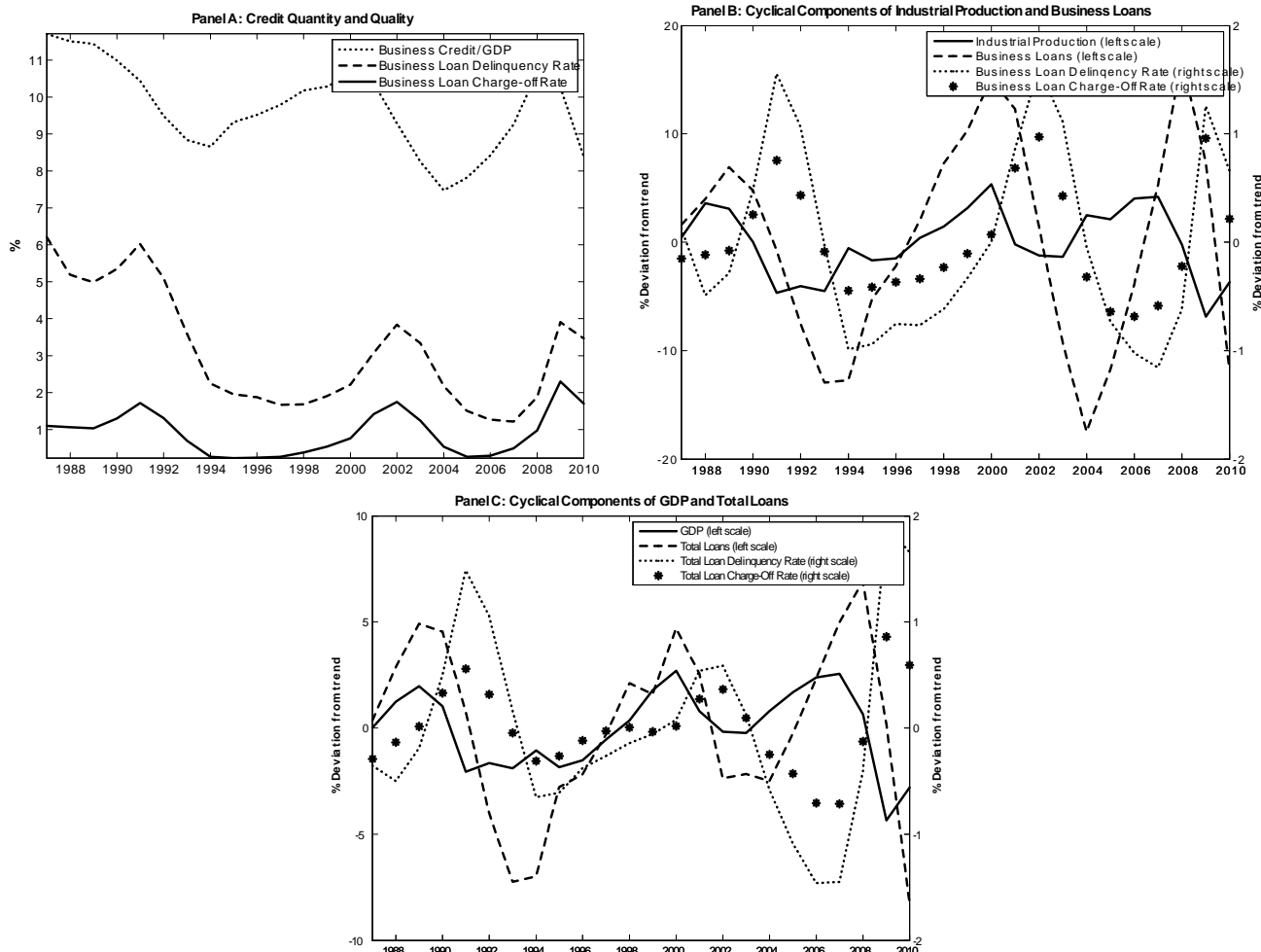


Figure 2.2: **Facts about the Quantity and Quality of Credit.** Panel A plots the business credit to GDP ratio against the delinquency rate and the charge-off rates on commercial and industrial loans. Panel B plots the cyclical component of industrial production, the quantity of business credit, the delinquency rate and the charge-off rates on commercial and industrial loans. Panel C redoes Panel B with GDP and aggregate credit variables. The cyclical components were computed using the H-P filter with annual data and smoothing parameter 100. Data sources are listed in Appendix A.1.

with them during business cycle contractions. Panels B and C also show that bank credit (business or aggregate) is more volatile over the business cycle than industrial production or GDP. Turning to the quality of business credit, both the delinquency rate and the charge-off rate are less volatile than production, and both variables lag the business cycle.

Tables 2.1 and 2.4 document numerically the patterns of Figure 2.2. Table 2.1 reports the correlation between the quantity of credit and the credit quality data series at different lags. Credit quality is positively correlated with a lag to the quantity of credit series. Table 2.4 reports the volatility of credit and credit quality relative to industrial production and GDP. This table shows that credit tends to be more volatile than either productivity measure whereas the credit quality series are less volatile.

2.5.2 CALIBRATION

Table 2.2 summarizes my parameterization. I calibrate one period in the model to be one year and target averages of U.S. annual data from 1987-2010. Thus each stage in a period lasts 6 months. The calibration targets the model when productivity is at its long run mean. I calibrate to the case in which banks have limited liability and do not internalize the effect of their actions on the pool of available borrowers.

I set the exogenous borrowing rate i_b to an annualized 2.4%, matching the average real 6-month U.S. interbank rate since 1987. Exogenous separation probability μ is set to 45% so that in the model the percentage of the loan portfolio in the second stage that is carried over from the first matches the carry-over ratio of 71% reported by Bharath et al. (2009). To calibrate the fraction of unseizable output (κ), I target an average return on equity of 20%, which is the average return on bank equity for large universal banks in the period before the 2007 crisis (ECB 2010). The curvature

Table 2.1: Comovement of Quality & Quantity of Credit

Variable x	Cross Correlation of									
	Total Loans at time t with			Business Loans at time t with						
	$x(t-2)$	$x(t-1)$	$x(t)$	$x(t+1)$	$x(t+2)$	$x(t-2)$	$x(t-1)$	$x(t)$	$x(t+1)$	$x(t+2)$
Quality of Credit:										
Delinquency Rate on Total Loans	-0.66	-0.72	-0.27	0.47	0.76	-0.67	-0.48	0.07	0.7	0.79
Delinquency Rate on Business Loans	-0.51	-0.61	-0.19	0.5	0.8	-0.76	-0.61	0.002	0.66	0.86
Charge-off Rate on Total Loans	-0.61	-0.66	-0.18	0.51	0.72	-0.66	-0.44	0.15	0.75	0.8
Charge-off Rate on Business Loans	-0.58	-0.6	-0.08	0.59	0.77	-0.76	-0.48	0.21	0.8	0.83

Note: Annual data for years 1987-2010 (data sources are listed in Appendix A.1).
Data detrended with the Hodrick-Prescott filter with smoothing parameter 100.

Table 2.2: Calibrated Parameters

Parameter	Value	Target
θ	10.7	Ratio of capital to loans of 8.57% as in FRED, in model*: 8.53%
α	0.03	FRED's series of charge-off rates on Business Loans: 0.91%, in model*: 0.56%
i_b	0.01	2.4% annualized real 6-month U.S. interbank as in FRED
μ	0.45	Loans carried over of 71% as in Bharath et al. (2009), in model*: 72.2%
κ	0.9	Average return on equity of 20% as in ECB (2010), in model*: 25.1%
K_0	1	Normalize initial capital stock to 1
γ	0.04	Capital requirement set to 4% as Tier 1 capital in Basel I
ρ_z	0.73	Bianchi and Mendoza (2011) estimates for U.S. productivity
σ_z	0.009	Bianchi and Mendoza (2011) estimates for U.S. productivity
c	2.8	Standard deviation of Charge-Off Rate 0.0038 as in FRED

*Model values are computed for the case without shocks.

Note: More information about the data sources can be found in Appendix A.1.

parameter α is set so that the charge-off rate matches the 0.91% ratio reported in FRED's series of charge-off rates on Business Loans.¹⁶

I calibrate the technology parameter θ so the ratio of total bank capital over total credit in the model matches the ratio of aggregate total bank equity to assets of 8.57% that it is the average in FRED data over my sample period. This level of equity is

¹⁶In the model the charge-off rate is the aggregate loan amount that is not recovered, given a realized TFP shock, over the total value of the loans:

$$\frac{\int_0^{\tilde{\omega}} [\lambda(\omega) + \phi(\omega)] [(1 - \kappa)\theta\omega^\alpha z_t L_t - L_t] d\omega}{\int_0^1 [\lambda(\omega) + \phi(\omega)] L_t d\omega}$$

where $\tilde{\omega}$ is the cutoff type ω such that:

$$(1 - \kappa)\theta\tilde{\omega}^\alpha z_t L_t = L_t.$$

above the benchmark capital requirement I calibrate below and the model is able to target it because not all banks operate with a binding capital requirement constraint.

Initial capital is a scale variable in the objective function, so it does not affect the choice of either π_1 or π_2 . Thus, without loss of generality, I normalize it to 1 and let equation (2.26) govern its dynamics. I assume a capital requirement of 4%, which was the Tier 1 capital requirement under Basel I. Basel I was the regulation in effect over most of my sample period.

I follow Bianchi and Mendoza (2011) to calibrate the TFP process, adjusting the persistence, ρ_z , and variance of the shock process, σ_z^2 , to a semestral frequency since I have two shocks per period.¹⁷

The adjustment cost c is calibrated so that the standard deviation of the charge-off rate in the model matches the standard deviation of 0.0038 found in the data. The parameters π_1^{ss} and π_2^{ss} are the lending intensities computed in the model when productivity is at its long run mean.

2.5.3 QUANTITATIVE PROPERTIES OF THE MODEL

To simulate business cycles, I call each two-stage game a period and solve the model for many periods for the case with both frictions. Periods are connected by the laws of motion for aggregate productivity and bank capital. Because bank capital grows over time, model variables such as output and total credit are non-stationary. However, the banks' value functions are linear in capital, K_t , so banks' decisions are unaffected. I discuss further the methodology behind the simulations and how I detrend the non-stationary variables in Appendix A.2. I think of the model as a representative agent of the banking system.

¹⁷With this setup, the mean of the TFP process is normalized to equal 1. Calibrating this mean would be equivalent to changing our calibration of θ .

Table 2.3: Comovements in the Model

Variable x	Cross Correlation of Loans at time t with				
	$x(t-2)$	$x(t-1)$	$x(t)$	$x(t+1)$	$x(t+2)$
Quality of Credit:					
Charge-off Rate	-0.15	-0.30	-0.52	0.62	0.14
Note: Model simulated as discussed in Appendix A.2.					

Table 2.3 reports the correlation of the quantity of credit with the quality of credit from the model. I find that the model generates quality of credit measures which are positively correlated with a lag to the quantity of credit. In credit booms, banks extend a high quantity of low quality credit because they engage in more uninformed lending. That is, they promote giving credit above screening their borrowers. However, lower screening increases the probability of bank losses if the productivity next period is not as good as expected. Hence, periods of high credit volume are followed by periods with increases in loan losses, and we see the positive correlation with a lag. The negative contemporaneous correlation evident in Table 2.3 reflects that periods of large (small) losses caused by the aggregate shock process are associated with less (more) favorable expectations about lending prospects and thus less (more) credit. Similarly, large (small) losses in previous periods may mean that low (high) expectations and thus low (high) levels of lending persist for awhile.

Table 2.4 reports volatilities relative to output from the model. The model replicates fairly well the key volatility patterns from the data, namely that the quantity of credit is more volatile than output and that the quality of credit is less volatile. Two effects drive the movements in the quantity of credit: the level of bank capital which endogenously evolves following equation (2.26), and the choices of lending intensities

Table 2.4: Volatility

	In U.S. data		Model
	Std. Dev. relative to:		Competitive Eq'm
	GDP	Industrial Production	Std. Dev. relative to Output
Quantity of Credit:			
Total Loans	1.85	1.06	1.01
Quality of Credit:			
Charge-off Rate	0.16	0.1	0.01

Note: Annual data for years 1987-2010. Data detrended with the HP filter with smoothing parameter 100. Data sources are listed in Appendix A.1. Model simulated as discussed in Appendix A.2.

and the pivotal borrowers. The relative volatilities from the model also resemble the volatilities relative to industrial production.

2.6 OVERLENDING AND EXCESSIVE VOLATILITY

In this section, I use the calibrated model to examine the impact of each friction on screening and overlending. I then study how much excessive volatility each friction generates in the model.

2.6.1 OVERLENDING

Figures 2.3 and 2.4 report comparative statics exercises that illustrate each friction's individual effect on screening intensity in stage 1a. The top panels of Figure 2.3 compare the screening intensity from the models in which each friction operates by itself (solid blue lines) with that from the model in which neither friction operates (dotted red line) as a function of aggregate productivity. The bottom panels of Figure 2.3 plot the differences in screening intensity computed in the top panels. The panels on the left focus on limited liability as the unique friction. The panels on the right

focus on the lack of internalization friction. Figure 2.4 redoes Figure 2.3 but as a function of the cost of banks' borrowings.

To formulate the banks' value functions for the model in which neither friction operates, I impose that banks incorporate equation (2.29) in the equations of Section 2.4, thus eliminating the lack of internalization friction, and that the *max* operators ($\max\{0, (1 - \kappa)y(\omega, z_i, L_t) - (1 + i_b)B_t\}$ for $i = 1, 2$) are removed in favor of the banks' revenue function $((1 - \kappa)y(\omega, z_i, L_t) - (1 + i_b)B_t$ for $i = 1, 2$), thus eliminating limited liability. For the models in which each friction operates by itself, I simply make one of the aforementioned changes.

Screening intensity is always between zero and 0.5 because when TFP is high (or the cost of borrowings is very low) the pool of borrowers is highly profitable and banks choose to spend all of their resources on matching. However, when TFP is low enough (or the cost of borrowing is high enough) banks want to lend only to those borrowers they know are profitable and maximize their chances of making an informed match by choosing $\pi = 0.5$. I observe several results:

1) Both frictions imply too little screening. In the limited liability case, the banks face a truncated income function that encourages them to give too much credit. In the lack of internalization case, the banks do not take into account the negative effects of their lending decisions on the pool of borrowers.

2) Screening decreases as the cost of borrowings decreases or as TFP increases, with or without the frictions. The result shows that time varying lending standards should not be confused with "lax standards" because lending standards should change with macroeconomic conditions. Banks spend less time screening their borrowers to ensure profitability when the quality of the average borrower is higher or when it is less expensive to fund a loan. The problem is that in these times underscreening is

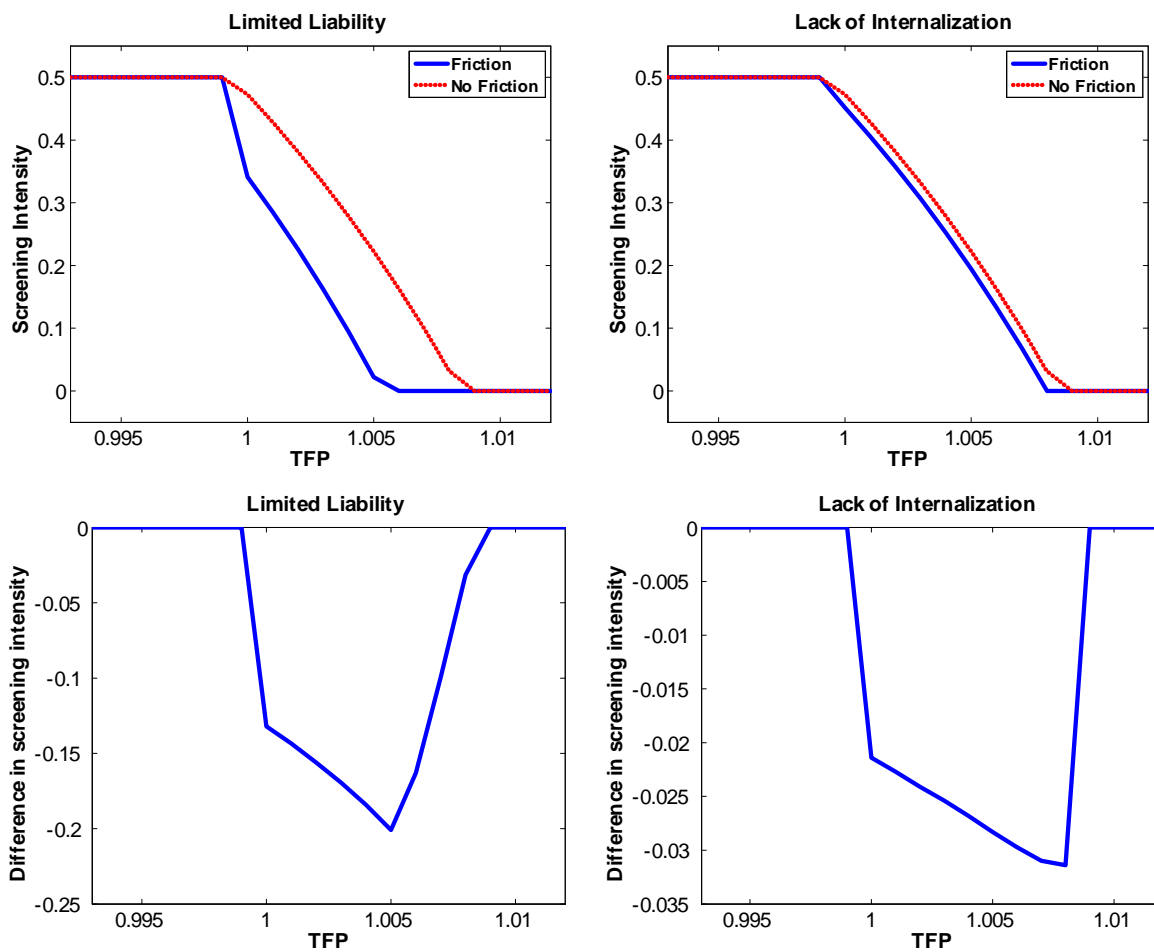


Figure 2.3: **Screening Intensity as a Function of Firm's TFP.** The panels on the top plot the screening intensity at stage 1a for the models with and without frictions as a function of firms' TFP. The panels on the bottom plot their differences. The panels on the left focus on limited liability as the unique friction. The panels on the right focus on lack of internalization of the effects on the quality of the borrower's pool.

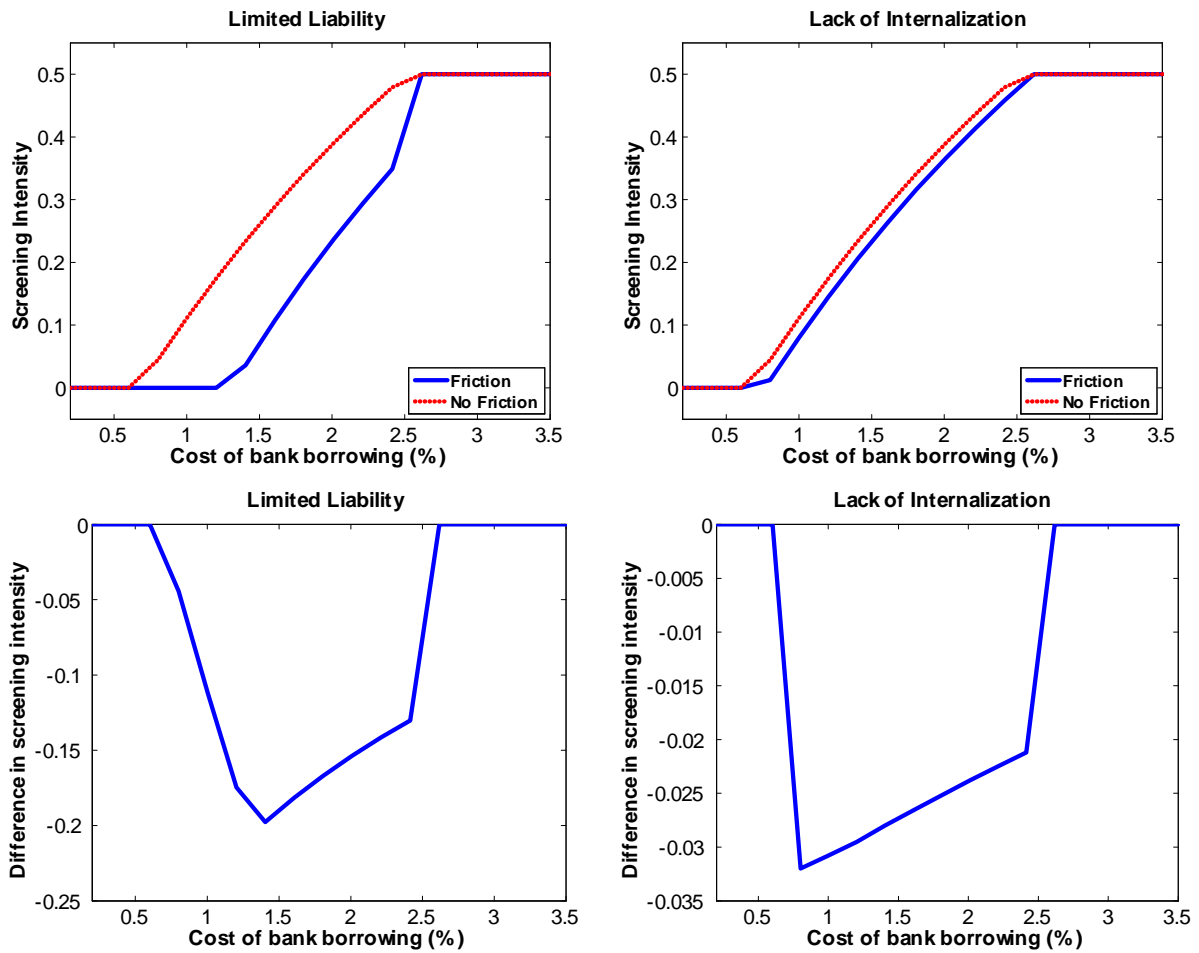


Figure 2.4: **Screening Intensity as a function of the Cost of Bank's Borrowings.** This figure redoes Figure 2.3 but as a function of the cost of borrowings for the banks.

a larger problem, i.e., the gap between screening when there is no friction and when there is a friction is larger (overlending is pro-cyclical).

3) In quantitative terms the underscreening generated by limited liability is larger than that which lack of internalization generates.

2.6.2 EXCESSIVE VOLATILITY

In this subsection I show that overlending generates amplification effects in response to economic shocks. Under both frictions banks do not internalize all the effects of their actions and are more exposed to uninformed credit than if the frictions were not there. Figure 2.5 plots this result. The upper left panel shows a positive TFP shock and the upper right panel shows the reaction in credit. The lower panels do the same thing for a negative TFP shock.

Being overexposed to shocks is good in good times (higher credit means more profits after positive unexpected productivity shocks) but bad in bad times (higher credit means more losses when the shocks are bad). Thus, we see excessive volatility in banks' earnings. Given that banks' earnings determine the amount of capital available for lending in the future, and that the model requires credit in order to produce, all variables of an economy with frictions are more volatile than in an economy without them. Table 2.5 shows this result.

When I examine the impact of each friction individually in Table 2.6, I find that the limited liability friction induces more excessive volatility than does the lack of internalization friction. The relative volatilities of output and credit in the limited liability case are 19 percentage points higher than those of the lack of internalization friction. This happens because, as we saw in Figures 2.3 and 2.4, the limited liability friction generates more uninformed, low quality credit than does the other friction, so banks are more exposed to economic shocks.

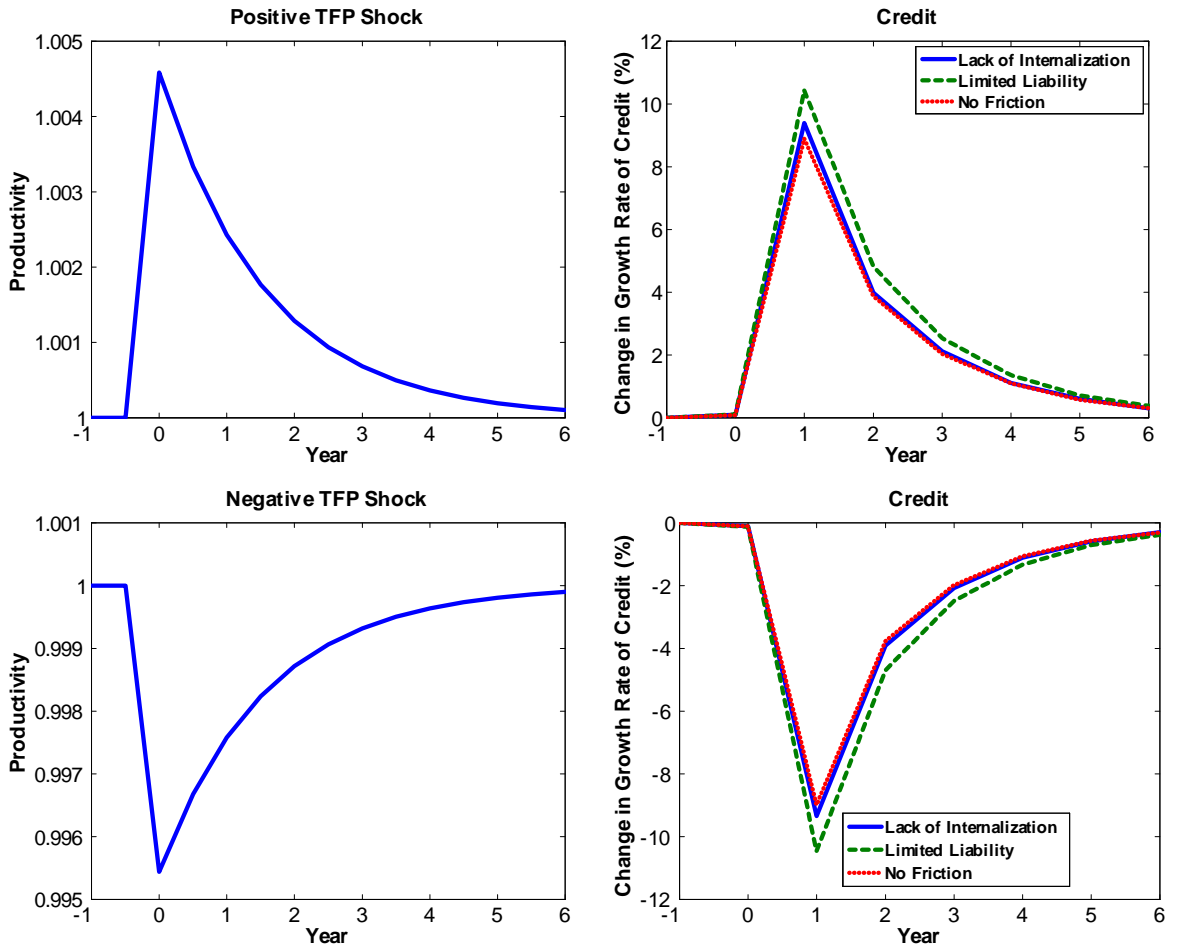


Figure 2.5: **Impulse Responses of Credit to TFP Shocks.** The panels on the left plot a positive (upper left panel) and a negative TFP shock (lower left panel). Then the panels on the right plot the associated response in credit for three different cases: 1) Model with only limited liability as friction, 2) model with only lack of internalization as friction, 3) model with no friction.

Table 2.5: Excessive Volatility over the Business Cycle

	Std. Dev.		Ratio Frictions to No Frictions
	Both Frictions	No Friction	
Output	0.355	0.263	1.348
Bank Profitability			
Return on Equity	0.226	0.187	1.208
Quantity of Credit			
Total Loans	0.357	0.266	1.345
Quality of Credit			
Charge-off Rate	0.002	0.001	1.193

Note: Model simulated as discussed in Appendix A.2.

Table 2.6: Excessive Volatility of each Friction

	Std. Dev. of model with friction/model without	
	Limited Liability	Lack of Internalization
Output	1.274	1.081
Bank Profitability		
Return on Equity	1.160	1.061
Quantity of Credit		
Total Loans	1.272	1.080
Quality of Credit		
Charge-off Rate	1.164	1.023

Note: Model simulated as discussed in Appendix A.2.

2.7 POLICY TOOLS

In this section I discuss three policy tools that help to mitigate overlending. One tool is capital requirements. Increasing them affects credit by reducing banks' external borrowings, thus banks reduce the size of their lending (equation 2.7). Moreover, higher capital requirements imply that a larger share of the loan is financed by bank's equity, thus the protection from limited liability is smaller (the bank has a larger percentage that it can lose). In addition, increasing capital requirements lower loan profits because banks are operating at smaller leverage ratios, so matching is less desirable and screening increases.

Another tool is a tax on banks' lending, τ_l . Under this policy, a bank's after-tax revenue from a loan is $(1 - \tau_l)(1 - \kappa)y(\omega, z_t, L_t)$. Since lending is less profitable, banks have less incentive to match and thus more to screen. Lastly, I consider a tax on banks' borrowings, τ_b , such that the after tax cost for banks of external financing is $(1 + \tau_b)(1 + i_b)B_t$. The tool encourages banks to screen more to ensure loans are profitable enough to repay their higher borrowing costs.

Capital requirements are the main tool in Basel III and an element of new banking regulation in most countries. However, several countries have implemented reserve requirements as a macroprudential tool (see Lim et al. 2011 for a survey). Reserve requirements may be thought of as a tax on banks' lending since they force banks giving credit to deposit extra money with the central bank at a rate lower than the lending rate. Finally, monetary policy affects banks in a way similar to a tax on borrowing since monetary policy alters the costs of banks' borrowings.

In Figure 2.6 I study how the policy tools affect total credit. I plot the level of credit in the competitive equilibrium with the frictions as a function of the policy tools in the economy with no shocks.

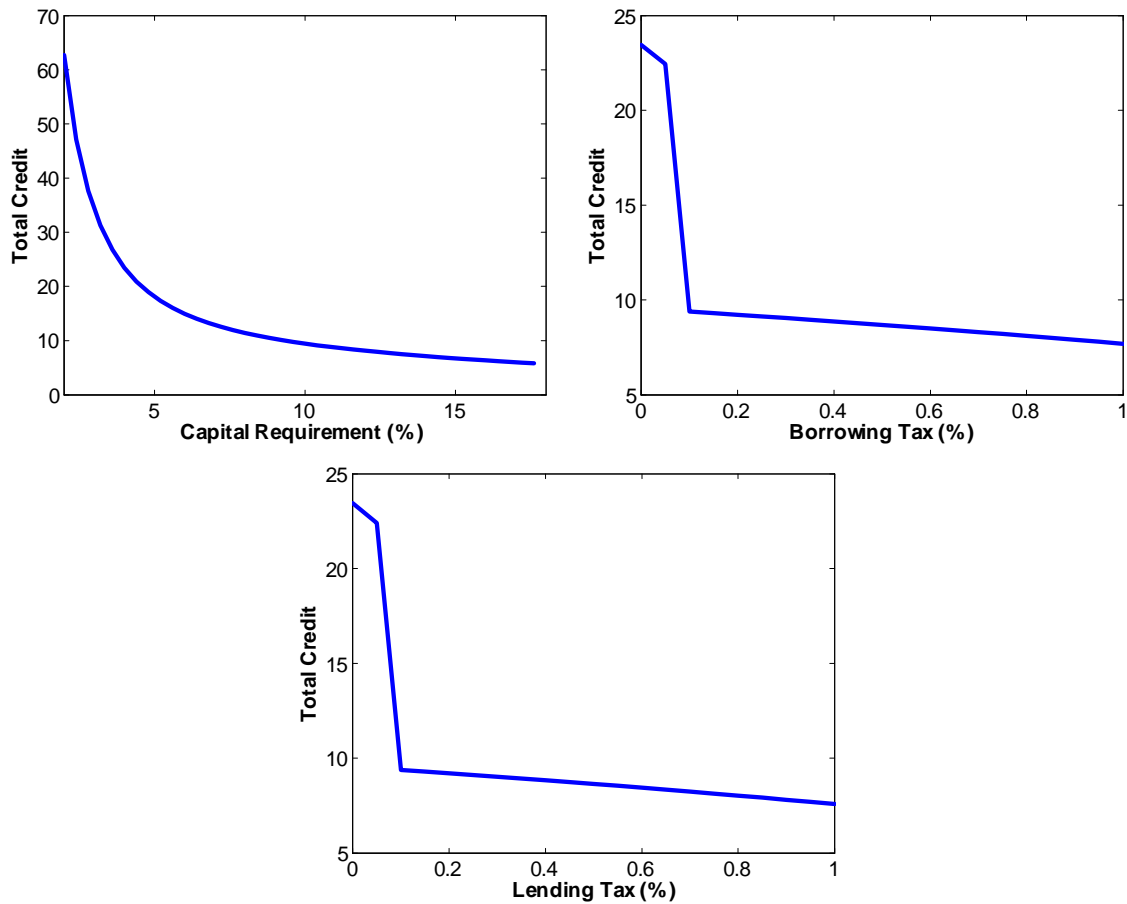


Figure 2.6: **Total Credit and Macroprudential Tools.** These figures plot the reaction of total credit to the three macroprudential tools: capital requirements, a tax on bank's borrowings and a tax on bank lending.

In all of the plots of Figure 2.6, total credit is monotonically decreasing in the level of the policy tool. Capital requirements generate a smooth decline in credit, whereas taxes have a more jagged effect. The reason behind this difference is that taxes affect the uninformed decision rule (equation 2.16 augmented with the appropriate tax regime), but capital requirements do not. Once taxes rise above 0.07% in the benchmark model, uninformed lenders stop lending. This generates the large decline in total credit evident in the tax plots. The capital requirement, on the other hand, is a scalar in the decision rule and plays no role in the cutoff of uninformed lending.¹⁸ I thus see a smooth decline in the level of total credit with this tool.

In Table 2.7 I compare the policy tools. For the benchmark parameterization and no shocks, I compute the change in capital requirements and in taxes needed to lower the amount of total credit by 5%. I find that capital requirements should increase from the benchmark of 4% to 4.17%. This change results in a slight increase in screening, a smaller loan size, and no change to the pivotal borrower. The tax rates on lending should increase from zero to 0.056% and those on borrowing from zero to 0.059%. Both taxes increase screening almost 10%, loan size remains unchanged, and the pivotal borrower increases by 1.7%.

An important distinction between the two types of policy tools can be seen in the performance of screening. The capital requirements lower total credit mostly by limiting loan size, with little support from higher screening intensity. Taxes, on the other hand, affect banker behavior by encouraging higher screening intensity and less matching, while loan size does not change.

¹⁸Similarly, capital requirements do not affect the pivotal borrower decision of informed lenders. However, capital requirements do affect the banks' objective function through the relationship between loan size and borrowings, so they affect the choice of screening and matching intensity.

Table 2.7: Comparing the Policy Tools

	Policy Target: lower total credit by 5%		
	Capital Req.	Borr. Tax	Lending Tax
Policy tool	4.173%	0.059%	0.056%
% change in Screening	2.01%	9.81%	9.81%
% change in Loan Size	-4.14%	0.00%	0.00%
% change in Pivotal Borrower	0.00%	1.72%	1.72%
% change in Uninformed Credit	-5.90%	-8.78%	-8.78%
% change in Informed Credit	-4.09%	-1.20%	-1.20%
% change in Total Credit	-5.00%	-5.00%	-5.00%
% change in Output	-4.99%	-4.96%	-4.96%

Note: Benchmark capital requirement is 4%; benchmark taxes are 0%.

The distinction can again be seen when I examine the effects of the policies on the types of credit available in the economy. I find that the taxes are better at getting rid of the type of lower-quality credit I do not want (the uninformed credit) without reducing the higher-quality credit I do want (the informed credit to the profitable ω types). In this sense, taxes are akin to a scalpel whereas capital requirements are a more blunt policy tool. The consequence can be seen in the change in output. For the same reduction in total credit, the taxes generate less reduction in output.

2.8 EMPIRICAL ANALYSIS

I conduct an empirical regression analysis to study whether there is an adverse impact of competition, measured by branch HHI, on lending standards, as is suggested by the model's lack of internalization friction. I also study whether this impact changes over the business cycle and across markets with different housing supply elasticities.

2.8.1 DATA

My principal data sets are publicly available and include U.S. home mortgage application data provided annually by the Home Mortgage Disclosure Act (HMDA) and bank branch data from the Federal Deposit Insurance Corporation's (FDIC) annual Summary of Deposits Survey. My database covers millions of mortgage applications and tens of thousands of bank branch locations from the 366 Metropolitan Statistical Areas (MSAs) across the U.S. for the years 2005-2011. I aggregate these observations to the MSA level to conduct my analysis. I compute annual denial rates on mortgage loan applications for each MSA from HMDA and an annual measure of bank branch concentration for each MSA from the Summary of Deposits Survey. My control variables are measured at the MSA-level and include population and average per capita personal income from the Bureau of Economic Analysis as well as home price index data from Freddie Mac.^{19,20} I also utilize housing supply elasticity data provided by Saiz (2010) for a subsample of MSAs. In what follows, I define a bank or a lender as the regulatory top holder financial institution. That is, where possible I aggregate observations up to the bank holding company level. Table 2.8 reports summary statistics.²¹

To conduct my analysis, I focus on local mortgage lending by commercial banks and savings institutions. A mortgage loan application is considered to be local if

¹⁹Average per capita personal income is the total personal income of the residents of a given MSA divided by the resident population of that MSA. Total personal income is the sum of wage and salary disbursements, supplements to wages and salaries, proprietors' income, dividends, interest, and rent, and personal current transfer receipts, less contributions for government social insurance.

²⁰Freddie Mac Home Price Index (HPI) data is reported monthly. I use December data from each year to compute the annual percentage change in house prices for each MSA. I also ran my analysis using FHFA HPI data and found similar results. The Case-Shiller HPI is another widely-used metric, however it is available for only 20 MSAs.

²¹Further details about the data sources can be found in Appendix A.1.

Table 2.8: Summary Statistics

Variable Name	Description	Obs.	Mean	Std. Dev.	Min	Max
$denial_rate_{kt}$	Denial rate on mortgage applications	2,562	0.129	0.054	0.016	0.500
$branch_HHI_{kt}$	HHI based upon lender branch market shares	2,562	0.123	0.057	0.029	1.000
$\% \Delta HPI_{k,t-1}$	Percent change in house prices, lagged	2,562	0.006	0.090	-0.434	0.396
$income_{kt}$	Per capita personal income (in 000s)	2,562	35.264	6.770	17.286	80.139
$\ln(pop_{kt})$	Log of population	2,562	12.661	1.059	10.919	16.761
$\% \Delta income_{kt}$	Percent change in per capita personal income	2,562	0.031	0.040	-0.224	0.331
$elasticity_k$	Housing supply elasticity	602	1.927	0.991	0.600	5.450

Note: Data for 366 MSAs from 2005-2011. k =MSA and t =year. See Section 2.8.1 for a description of the dataset.

the lender receiving the application has a physical branch in the same MSA as the property.²² Examining local lending behavior has two advantages in the context of this analysis. First, it is likely that lenders compete differently for local loans than for non-local loans. For example, physical branch locations are important to attract local mortgage customers, but would not provide a benefit for non-local lending. That is, customers who apply for loans locally are likely influenced by the proximity and number of a particular lender's branches. Moreover, lenders' branches may be a good proxy for competition when analyzing mortgage denial rates because they are less affected by endogeneity than a measure based upon the market share of mortgage applications received or loans granted. Because of these reasons, I construct my measure of lender concentration using a Herfindahl-Hirschman Index (HHI) based on lenders' branch market shares for each MSA in each year. This index is a measure of the amount of competition among lenders' physical branch locations and takes on values between 0 and 1. Larger values of the branch HHI indicate market concentration, or the presence of a few dominant lenders that operate the majority of branches in an MSA. Smaller values indicate more competition among lenders with no dominant players. Second, local lenders may have more information, arising from operations within a given MSA, with which to make local lending decisions than non-local lenders. Studying local lending thus ensures some level of consistency in lender behavior within each MSA.

HOME MORTGAGE DISCLOSURE ACT (HMDA) DATA

The Home Mortgage Disclosure Act was enacted in 1975, and requires mortgage lending institutions to report data on mortgage loan applications annually to gauge

²²Rosen (2011) and Cortes (2012) also study the behavior of local lenders in the mortgage market.

compliance with fair lending laws and to guide public investment in housing. The data coverage includes mortgage applications received by depository institutions and mortgage finance companies with branch offices in MSAs. The data do not cover mortgage applications received by small or primarily rural depository institutions.

HMDA data include characteristics about mortgage loan itself, information regarding whether the loan was approved or denied, borrower demographic and income characteristics, and information regarding the underlying property and its location. My sample starts in 2005 and runs through 2011. HMDA data cover approximately 95% of the total volume of home mortgage originations in the U.S. in this period.²³ Because my measure of competition is based upon branching data that is only available for banks and savings institutions, I restrict my analysis to the mortgage application data reported by these institutions. With this restriction, my data account for approximately 40% of the lending activity captured by HMDA. The remaining fraction of lending activity was reported by mortgage finance companies, for which there is unfortunately no data on physical office locations.

My primary interest in the HMDA data is computing the denial rate of mortgage applications in a particular MSA in a particular year. To ensure that my comparison of denial rates across MSAs is sensible, I restrict my analysis to applications of a similar type: conventional home purchase loans where the underlying property is a one-to-four family home that will be owner-occupied. Furthermore, I examine only those applications with clear approval or denial decisions. That is, I include applications in my dataset where the lender either originated the loan, denied the loan, or the loan was approved but not accepted. My computation of the denial rate is the total number of applications denied in a particular MSA in a particular year divided by the total number of applications received in a particular MSA in a particular year.

²³Dell’Ariccia et al. (2008) provide estimates of HMDA coverage rates by year.

SUMMARY OF DEPOSITS SURVEY DATA

The Summary of Deposits Survey contains data on the location and deposits of branch offices for all FDIC-insured institutions as of June 30th of each year. I compute the total number of branch offices in an MSA for each HMDA lender in a given year. I then compute each lender's branch market share, or the number of branches operated by that lender divided by the total number of branches in the MSA. I square these branch market shares and add them up within each MSA to compute lenders' branch concentration, or branch Herfindahl-Hirschman Index (HHI). The formula for branch HHI is thus:

$$branch_HHI_{kt} = \sum_{i=1}^{n_k} \left(\frac{branches_{ikt}}{branches_{kt}} \right)^2 \quad (2.37)$$

where i = lender, k = MSA, t = year and n_k = the number of lenders in MSA k .

2.8.2 EMPIRICAL METHODOLOGY

My empirical regression analysis tests the relationship between market concentration and lending standards in the U.S. mortgage market. My baseline specification is as follows:

$$\begin{aligned} denial_rate_{kt} = & \alpha_t + \beta_1 branch_HHI_{kt} + \beta_2 \% \Delta HPI_{k,t-1} + \beta_3 income_{kt} + \\ & + \beta_4 \% \Delta income_{kt} + \beta_5 \ln(pop_{kt}) + \varepsilon_{kt} \end{aligned} \quad (2.38)$$

where k = MSA and t = year. The left-hand side variable is the denial rate, which measures lending standards within the MSA in a given year. I regress this on my main variable of interest, $branch_HHI_{kt}$, which is the Herfindahl-Hirschman Index (HHI) of lenders' branch market shares with the MSA in a given year, as well as various controls. The model implication I am testing is whether more market concentration (less competition) implies higher denial rates. Because my data sample includes the recent

financial crisis period, I include year dummies (α_t) to capture nationwide changes in mortgage market conditions. I control for changes in house prices ($\% \Delta HPI_{k,t-1}$) and average per capita personal income ($\% \Delta income_{kt}$) at the MSA-level. Because rising prices and income improve borrower creditworthiness, I expect the coefficients on these terms to be negative. The change in house prices enters the equation with a lag to rule out endogeneity bias, as lower denial rates within an MSA may increase the demand for housing and, therefore, increase house prices in that area. I also control for the level of average per capita personal income ($income_{kt}$, measured in thousands), expecting areas with a higher level of income to exhibit lower denial rates. I also include the log of population ($\ln(pop_{kt})$) as a measure of market size. These controls are also used by Dell’Ariccia et al. (2012).

A secondary, but related, implication drawn from the model’s lack of internalization friction can be tested using my data set. In the model, the degree to which lending standards in a monopoly market are higher than those in a perfectly competitive market changes over the business cycle. For example, in the lower right panel of Figure 2.3, we saw that difference in lending standards between a perfectly competitive market and a monopoly market is largest when TFP is relatively large. Therefore, if this model conclusion is correct, we would expect to see that a negative effect of competition on denial rates is larger the higher is borrower income. I test this hypothesis by adding an interaction term to my baseline specification that relates branch HHI with changes in income:

$$\begin{aligned}
 denial_rate_{kt} = & \alpha_t + \beta_1 branch_HHI_{kt} + \beta_2 \% \Delta HPI_{k,t-1} + \beta_3 income_{kt} + \\
 & + \beta_4 \% \Delta income_{kt} + \beta_5 \ln(pop_{kt}) + \beta_6 (branch_HHI_{kt} * \% \Delta income_{kt}) + \varepsilon_{kt}
 \end{aligned}
 \tag{2.39}$$

where $k = \text{MSA}$ and $t = \text{year}$. The effect of branch HHI on the denial rate under this specification is $\frac{\partial \text{denial_rate}_{kt}}{\partial \text{branch_HHI}_{kt}} = \beta_1 + \beta_6 \% \Delta \text{income}_{kt}$. If β_1 is positive as hypothesized, then a positive β_6 would imply that on the positive side of the business cycle, the effect of market concentration on lending standards is even stronger (more positive). That is, a positive β_6 would support the theory and, thus, the finding of Figure 2.3. A negative β_6 , on the other hand, would imply a lesser positive or even negative effect of market concentration on lending standards on the positive side of the business cycle. As before, I would expect the coefficients on changes in house prices and income to be negative, because rising prices and income improve borrower creditworthiness and lead to lower denial rates.

To further analyze the relationships I observe above, I also explore whether the competition-lending standards relationship changes with the elasticity of the housing supply in a given market. For example, competition in markets where lenders are financing a more established housing stock may have a different effect on lending standards than competition in markets where lenders are financing an expanding housing stock. For example, we could think that there is a higher information content of applications filed in an MSA with a more established housing stock. Thus, it seems important to control for this channel in my analysis. I borrow measures of housing supply elasticity from Saiz (2010). My specification takes the following form:

$$\begin{aligned} \text{denial_rate}_{kt} = & \alpha_t + \beta_1 \text{branch_HHI}_{kt} + \beta_2 \% \Delta \text{HPI}_{k,t-1} + \beta_3 \text{income}_{kt} + \\ & + \beta_4 \% \Delta \text{income}_{kt} + \beta_5 \ln(\text{pop}_{kt}) + \beta_6 (\text{branch_HHI}_{kt} * \text{elasticity}_k) + \varepsilon_{kt} \end{aligned} \quad (2.40)$$

where $k = \text{MSA}$, $t = \text{year}$, and I have added an interaction term that relates branch HHI with Saiz's supply elasticity measure to my baseline specification. Under this specification, the effect of branch HHI on the denial rate is $\frac{\partial \text{denial_rate}_{kt}}{\partial \text{branch_HHI}_{kt}} =$

$\beta_1 + \beta_6 elasticity_k$. Similar to the analysis above, if β_1 is positive as hypothesized, a negative coefficient on the interaction term would imply a weaker positive or negative relationship between denial rates and lender concentration as house supply elasticity rises. That is, such result would suggest that the effect of competition on lending standards is lower in MSAs where the housing stock elastic. A positive β_6 , however, would imply that the effect of competition on lending standards is stronger in those markets.

2.8.3 EMPIRICAL RESULTS

I estimate equations (2.38), (2.39), and (2.40) using OLS. The results are produced in Table 2.9. All three specifications lend support to the main implication of the lack of internalization friction. That is, I find MSAs in which market concentration (branch HHI) is high exhibit higher denial rates. This result is significant at the 1% level.

This finding contradicts that of Dell’Ariccia et al. (2012). In that paper, the authors use a measure of the Herfindahl-Hirschman Index based upon the market shares of loans granted in an MSA and find that loan denials are higher in more competitive markets. However, this result is only significant for data taken from the subprime mortgage market and is insignificant for the prime market.

Turning to the control variables, as expected, positive house price movements and higher levels of average per capita personal income are associated with lower denial rates across the three specifications. MSAs with larger populations tend to exhibit higher denial rates. Surprisingly, positive changes in average per capita personal income are associated with higher denial rates in the results of my baseline specification (column 1). This result is significant at the 10% level. However, in the other two specifications, there is no significant effect of changes in income on the

Table 2.9: Regression Results

	(1)	(2)	(3)
Dep. Var.: Denial Rate	All MSAs	All MSAs	MSAs with Saiz measure
Branch HHI	0.213*** (0.018)	0.210*** (0.024)	0.443*** (0.050)
% change in house prices, lagged	-0.065*** (0.015)	-0.066*** (0.015)	-0.054** (0.022)
Per capita personal income (in 000s)	-0.002*** (0.0002)	-0.002*** (0.0002)	-0.004*** (0.0003)
% change in personal income	0.073* (0.042)	0.059 (0.070)	0.014 (0.071)
Log population	0.017*** (0.001)	0.017*** (0.001)	0.030*** (0.002)
Year = 2006	0.010*** (0.004)	0.010*** (0.004)	0.020*** (0.006)
Year = 2007	0.021*** (0.004)	0.021*** (0.004)	0.042*** (0.006)
Year = 2008	0.024*** (0.004)	0.024*** (0.004)	0.039*** (0.006)
Year = 2009	0.029*** (0.005)	0.029*** (0.005)	0.026*** (0.009)
Year = 2010	0.037*** (0.004)	0.037*** (0.004)	0.038*** (0.006)
Year = 2011	0.046*** (0.004)	0.046*** (0.004)	0.053*** (0.007)
Branch HHI * % change in income		0.116 (0.459)	
Branch HHI * supply elasticity			-0.081*** (0.021)
Constant	-0.054*** (0.014)	-0.053*** (0.014)	-0.206*** (0.032)
Observations	2,562	2,562	602
R-squared	0.202	0.202	0.411

See Section 2.8.1 for a description of the dataset and Section 2.8.2 for the regression equations. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

denial rate, suggesting that this result may not be very robust. There does appear to be a systematic increase in the denial rate across the years of my sample, as evidenced by the increasing coefficients on the year dummies in columns (1) and (2) of Table 2.9. However, this pattern is not present in my specification that includes the Saiz (2010) elasticity measure.

In column (2), the addition of the interaction term relating branch HHI and changes in average per capita personal income from regression equation (2.39) only slightly alters the results of my baseline specification. The coefficient on the interaction term itself is positive but insignificant. This result implies that the stage of the business cycle has no impact on the relationship between competition and lending standards.

The third column of Table 2.9 presents the results of regression equation (2.40). Because Saiz (2010) provides the housing supply elasticity measure for only a subsample of MSAs, my sample size for this regression is smaller than the previous two regressions. Nonetheless, I find similar results. In addition, the sign of the coefficient on the interaction term of branch HHI with supply elasticity is negative, meaning that the concentration-lending standards relationship is weaker, but still positive, in more elastic markets.²⁴ This result implies, for example, that market concentration has a more positive effect on lending standards in markets like Miami than in markets like Indianapolis. The converse is also true—more competition implies a more negative effect on lending standards in Miami than in Indianapolis.

²⁴I verify that the concentration-lending standards relationship remains positive by computing the overall effect of branch HHI on the denial rate and inputting the supply elasticity measure from the most elastic market (5.45 for Wichita, KS). I have that $\frac{\partial \text{denial_rate}_{kt}}{\partial \text{branch_HHI}_{kt}} = 0.443 - 0.081 * 5.45 = 0.00155$.

2.8.4 ROBUSTNESS

I conduct multiple robustness checks using different measures of the house price index and different lags of changes in house prices and average per capita personal income. Here, I report the results of a robustness check to ensure the timing of my sample does not drive my results. The results of this exercise are reported in Table 2.10.

I split my sample into a pre-crisis sample, composed of observations from 2005-2007, and a post-crisis sample, composed of observations from 2008-2011, to verify whether the empirical support I find in the previous section is present in both periods separately. That indeed appears to be the case. The coefficients on branch HHI are positive across the three specifications in both time periods. The housing supply elasticity result, however, only holds in the post-crisis period. Interestingly, I find a significant (at the 5% level) positive coefficient on the interaction of branch HHI with change in per capita personal income during the 2008-2011 time period (column 5). This result supports the model implication that on the positive (negative) side of the business cycle, the effect of market concentration on lending standards is stronger (weaker). However, this coefficient is negative and insignificant for the pre-crisis period (column 2).

The behavior of the coefficients on lagged changes in house prices in Table 2.10 reflect the fact that my sample covers portions of the housing boom as well as the bust. Denial rates are increasing over the years of my sample, so the fact that the coefficients on $\% \Delta HPI_{k,t-1}$ are positive in the pre-crisis period and negative in the post-crisis period simply shows the changing direction of house prices.

Table 2.10: Robustness Check

	(1)	(2)	(3)	(4)	(5)	(6)
	Years 2005-2007 only			Years 2008-2011 only		
Dependent Variable: Denial Rate	All MSAs	All MSAs	MSAs with Saiz measure	All MSAs	All MSAs	MSAs with Saiz measure
Branch HHI	0.175*** (0.024)	0.219*** (0.051)	0.556*** (0.083)	0.199*** (0.027)	0.171*** (0.030)	0.152*** (0.071)
% change in house prices, lagged	0.067*** (0.019)	0.067*** (0.019)	0.018 (0.034)	-0.212*** (0.023)	-0.218*** (0.023)	-0.191*** (0.034)
Per capita personal income (in 000s)	-0.002*** (0.0002)	-0.002*** (0.0002)	-0.003*** (0.0005)	-0.002*** (0.0002)	-0.002*** (0.0002)	-0.004*** (0.0004)
% change in personal income	0.103* (0.061)	0.225 (0.142)	0.095 (0.096)	0.086 (0.057)	-0.067 (0.088)	-0.088 (0.104)
Log population	0.018*** (0.002)	0.017*** (0.002)	0.032*** (0.003)	0.014*** (0.001)	0.013*** (0.001)	0.026*** (0.003)
Branch HHI * % change in income		-0.991 (1.040)			1.275** (0.552)	
Branch HHI * supply elasticity			-0.053 (0.034)			-0.056** (0.027)
Constant	-0.068*** (0.018)	-0.072*** (0.019)	-0.273*** (0.049)	0.023 (0.019)	0.028 (0.019)	-0.089** (0.038)
Observations	1,098	1,098	258	1,464	1,464	344
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.167	0.168	0.416	0.216	0.219	0.445

See Section 2.8.1 for a description of the dataset. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

2.9 CONCLUSIONS

I have studied two frictions that lead banks to allocate too few resources to screening borrowers and too many to giving credit. The first friction, limited liability, leads to overlending by truncating banks' income distribution. In contrast, the failure of competitive banks to internalize how credit decisions affect the pool of borrowers leads to overlending by encouraging banks to favor lending today over the potential for profitable lending tomorrow. In quantitative terms, I find limited liability to be the larger friction. Both frictions generate excessive volatility in the business cycles of banking variables and aggregate output.

The three policy tools (capital requirements and taxes on banks' lending and borrowings) combat the frictions by encouraging banks to screen more and should be state-contingent because the frictions vary with macroeconomic conditions. For example, in good times regulators should "lean against the wind" and increase capital requirements or bank taxes. In quantitative terms, I find that taxes are better tools than capital requirements because they do not reduce the size of the loans going to the more productive agents.

I conduct an empirical regression analysis to study whether there is an adverse impact of competition, measured by branch HHI, on lending standards, as is suggested by the model's lack of internalization friction. I also study whether this impact changes over the business cycle and across markets with different housing supply elasticities. Using data from the U.S. mortgage market, I find support for such conclusions. Denial rates are lower in markets with lending environments that are more competitive. This result contradicts those found in other studies using HMDA data but is in line with the debate in the empirical banking competition-stability literature. Moreover, I find

that the negative relationship between competition and lending standards is stronger in markets where the housing supply is inelastic.

CHAPTER 3

LENDING STANDARDS AND COUNTERCYCLICAL CAPITAL REQUIREMENTS UNDER IMPERFECT INFORMATION

3.1 INTRODUCTION

Lax lending standards are usually blamed for over-exposing banks to risk.¹ In this chapter I propose a model of lending standards and two reasons why lending standards may be inefficient. Then I show that the model can replicate empirical patterns of credit booms and busts, use the model to conduct a quantitative study of early-warning risk indicators and analyze a Value-at-Risk (VaR) rule to implement countercyclical capital requirements. I show that capital requirements should be state-contingent and lean against lenders' beliefs by tightening after periods of asset price growth. However, the relationship between asset price growth and financial risk is not monotone, and this should be integrated in the setting of the capital requirements and use of early-warning indicators. I apply the model to the countercyclical capital buffer (CCB) proposed by Basel III for banks, but the model would also apply to other financial institutions that are now subject to capital requirements, such as mutual funds or broker dealers.²

¹For example, Dell'Ariccia et al. (2012), Demyanyk and Van Hemert (2011), Favilukis et al. (2012), Keys et al. (2010 and 2012) and Maddaloni and Peydro (2011) provide evidence of lax standards before the recent crisis. Corsetti et al. (1999) blame them for the Asian crises of the late 1990s.

²See Kramer et al. (2013) for a survey of capital rules on mutual funds, and Sacks (2013) for a study of SEC rules for broker-dealers.

The first reason lending standards are inefficient in the model is a truncation in lenders' return function such that lenders can take on leverage, but their maximum loss is their initial capital. This may be due to deposit insurance, government guarantees or limited liability. Each of these generates moral hazard on the part of the lenders and lax lending standards at all stages of the cycle relative to those of a regulator who fully absorbs all losses in excess of banks' equity.

The second friction leading to inefficient credit standards is imperfect information about the persistence of asset price growth. That is, asset prices are random and lenders cannot perfectly anticipate how persistent the prices will be. To make decisions, they form rational expectations using Bayes' rule. Lenders may have episodes of incorrect but rational beliefs in which optimistic (pessimistic) expectations lead them to take on too much (little) risk. Surveys of lending standards show that banks' expectations about economic activity and asset prices are among the main drivers of lending standards (ECB 2013).³

The interaction of moral hazard and imperfect information reinforces the need for regulation, as a regulator exposed to covering large depositor or bank creditor losses in the event that bank beliefs about asset price growth are wrong will be more cautious than banks operating under limited liability.

In the model there are lenders and heterogeneous borrowers who borrow to invest in projects whose returns depend on exogenous asset price growth. Lenders select their credit standards to ensure they only give credit to investors with a minimum level

³We are trying to capture the recent experience of Deutsche Bank in Spain. In 2007, its research department issued a report stating that "Spain's economic success over the past years has been most impressive... GDP growth is likely to remain above the euro-area average of just below 2% for several more years, allowing Spain to climb past Italy and Germany in the rankings of GDP per capita by 2020" (Deutsche Bank 2007). What happened in the following years suggests that Deutsche Bank had incorrectly overestimated the persistence of Spanish growth and had overlent.

of idiosyncratic characteristics. For example, through adequate screening the lender can ensure it lends only to borrowers with a minimum skill level, credit score or past success record. Lending standards change with expectations of asset price growth. When lenders expect growth to be high, all borrowers will be more profitable (bad investments are less bad in an environment of expected price increases) and lenders relax their standards to save on screening costs and maximize their chances of giving credit.

Capital requirements operate via two channels. First, higher requirements reduce leverage, thus limiting the expansion of banks' balance sheets during the credit boom and ensuring banks can absorb more losses in a downturn. Second, capital requirements affect the incentives behind banks' lending standard decisions via two opposing mechanisms. On one side, when capital requirements go up, banks' leverage and profits per unit of capital go down. Thus, there is less incentive for banks to pay the cost of implementing high lending standards. On the other side, because capital is more expensive than debt, when capital requirements go up the cost of banks' funds go up and banks need to raise their standards and be pickier to remain profitable. This last mechanism is quantitatively the strongest in the calibrated model.

The model could be calibrated to any asset price or income growth process. Due to the large role played by housing in the recent crisis, I calibrate it to match long-term averages of housing prices and U.S. banking data. I show that it can replicate patterns of recent credit boom episodes documented by Elekdag and Wu (2011).

I then study which patterns of real estate price growth and banks' beliefs could serve as early-warning indicators of a crisis. I find a non-linear relationship between real estate price growth, banks' optimism and the risk of bank losses that are in excess of banks' equity. There are two opposing forces at work. Higher real estate price growth makes banks optimistic about the persistence of price growth, causing

them to lower lending standards and become more exposed to risks. But these risks are also smaller because it is usually the case that rational banks are more optimistic in times when it is less likely a bad shock will happen. Thus, the maximum risks arise during price booms that occur in a middle ground. They are large enough to generate optimistic bank beliefs, but not large enough such that the likelihood of a bad shock is small. This middle ground in the calibrated model means two years of 5% price growth.

Finally, I analyze a VaR rule to implement the CCB. That is, under VaR the regulator adjusts capital requirements to ensure the probability that banks do not have enough equity to cover a given percentage of their losses is fixed at a certain level. The VaR rule implied by the model says that the regulator should increase the CCB when higher real estate prices lead to higher risk. Again, however, this relationship is not monotone. Higher prices lead banks to relax standards, thus building risk. However, if the price growth is very large, in a rational model it is very unlikely that this comes from bad fundamentals, thus a hard landing is less likely because the risk of a bad shock is smaller. Overall, I find that usually the first force dominates and more optimism means more risk for the regulator. Thus, I find that optimal regulation should lean against banks' beliefs, tightening in periods of optimism after increased real estate price growth, and relaxing in periods of pessimism after price downturns. Although, I do find the rule should be applied non-linearly.

The structure of the chapter is the following. Section 3.2 reviews the related literature. Section 3.3 presents the model. Section 3.4 characterizes the lending standards decision. Section 3.5 calibrates the model and studies its quantitative properties. Section 3.6 analyzes which patterns of real estate growth induce larger financial risks. Section 3.7 contains the VaR implementation of the CCB. Section 3.8 concludes.

Appendix B defines the variables used to calibrate the model and contains the numerical algorithm.

3.2 RELATED WORK

The chapter is related to several literatures. In terms of objectives, it complements a growing literature that studies the design of countercyclical capital regulation. Recent examples include Aliaga-Díaz and Olivero (2011), Aliaga-Díaz et al. (2011), Angeloni and Faia (2013), Gersbach and Rochet (2012), Malherbe (2013), Martinez-Miera and Suarez (2012), Repullo and Suarez (2013), and Repullo (2013), among others. I believe that I contribute to this literature through the mechanisms in the model, the model's quantitative implications which allow me to study counterfactuals, and the model's applications to studying early-warning indicators of risk and designing rules for the state-contingent capital requirements.

First, in terms of the mechanisms of the model, I analyze the use of capital regulation as a macroprudential tool to dissuade banks from taking on excessive risk (lax lending standards) during the build-up phase of the cycle. In this regard, the message of the chapter is related to papers that have discussed the connection between capital requirements and bank incentives (for example, Allen et al. 2011, Dell'Ariccia and Marquez 2006, Di Iasio 2013, Holmström and Tirole 1997, Koehn and Santomero 1980, and Mehran and Thakor 2011). The model does not have the elegant closed form results of these papers, but in exchange it allows me to study quantitatively the interaction between limited liability and the way rational banks form beliefs in an environment of imperfect information. This process of bank belief formation has not been studied much in the banking literature.

Also in terms of the model, I propose a new way of modeling lending standards. In the model tighter standards means that banks are pickier and raise the threshold that qualifies a borrower for credit. Most of the literature models lending standards as a creditworthiness test, for example Broecker (1990), Gorton and He (2008), Ruckes (2004) or Thakor (1996). That is, tighter standards means that the banks screen more and are more likely to discover the true type of their borrowers. In those models the income threshold to qualify for credit does not change. Instead, the amount of effort to discover the type of the borrower changes. Thus, lax standards in the model captures something different. In a model of lending standards as a creditworthiness test, lax standards means banks qualify more borrowers because they did not screen them enough to discover they were bad. In the model, lax standards means banks give credit to lower quality borrowers even if they know the income of the borrower.⁴

Second, I analyze house price growth as an early-warning indicator of increased banking system risk. Implementing the CCB requires that regulators identify data-based indicators that illustrate when credit growth is excessive. Basel III proposes the deviation from trend in the credit-to-GDP ratio as a primary indicator. However, Edge and Meisenzahl (2011) and Repullo and Saurina (2011) present some drawbacks to reliance on this credit-to-GDP gap.⁵ Using data from the EU, recent empirical work by Behn et al. (2013) shows that using equity prices, house prices and banking sector

⁴Our modeling assumption is inspired by the new literature on trade (Melitz 2003, Eaton and Kortum 2004). In new trade models, only the most productive firms decide to export, and in our model, the banks decide who are the most productive borrowers qualified for a loan.

⁵Edge and Meisenzahl (2011) find that real-time estimates of the credit-to-GDP gap differ from final estimates and that these differences can be quite large. The authors argue that regulatory reliance on a real-time credit-to-GDP gap can induce policy action when final estimates of the gap would not, generating an unnecessary drag on the economy. Repullo and Saurina (2011) argue that use of the credit-to-GDP gap may in fact worsen the pro-cyclicality of capital regulation because for many countries the variable is negatively correlated with GDP growth.

variables in addition to aggregate credit variables improves the predictive power of CCB early-warning models. Smith and Weiher (2012) also argue that a key risk driver is the deviation of the house price index from its trend (a variable that may capture over-optimistic expectations) and propose a methodology to implement countercyclical capital requirements based upon this variable. Their analysis is empirical, while mine employs a calibrated model.⁶

Third, I propose a VaR rule to set capital requirements. Basel III does not provide much guidance on how to implement changes in the CCB other than some thresholds related to the credit-to-GDP gap. In that regard I contribute to the debate on what rules to follow to apply macroprudential policy tools. The use of a VaR approach to design the regulatory capital requirements complements models where individual banks use a VaR framework to determine their desired capital levels, such as Di Iasio (2013), Gordy (2003) or Shin (2012). The VaR framework captures the risks for regulators from imperfect information well and shows that the relationship between asset price growth and financial risk is not monotone.

3.3 MODEL

In every period t there is a continuum of mass one of borrowers and another continuum of financial institutions. I will refer to the financial institutions as banks, although there is nothing in the model that distinguishes them from private equity funds, mutual funds, broker dealers or some other type of financial institution that lends or invests. The banks can be thought of as a representative bank because I abstract from strategic interactions between them.

⁶Some countries, such as Switzerland and Norway, are using real estate price growth as an early-warning indicator although their methodologies are not described in detail (Swiss National Bank 2013, Olsen 2013).

Borrowers borrow from the banks and invest in projects whose return depends on asset price growth. This price growth is exogenous in the model and subject to persistent and non-persistent shocks. Only the sum of these two shocks is observable, and banks solve a signal extraction problem to infer how persistent asset prices will be.

I simplify the model on the borrowers' side and on the price of credit to focus on the banks' lending standards decisions. The endogenous variables of interest are lending standards, the amount of credit, borrowers' output, non-performing loans, delinquency rates, the quality of banks' portfolios, and banks' return on equity.

3.3.1 BORROWERS AND LENDING STANDARDS

Borrowers are heterogeneous in the parameter ω and if they qualify for credit they receive the amount L_t . A borrower of type ω who invests L_t dollars in a project receives earnings of

$$y(\omega, \frac{p_t^h}{p_{t-1}^h}, L_t) = \frac{p_t^h}{p_{t-1}^h} \omega^\alpha L_t, \quad (3.1)$$

where $\frac{p_t^h}{p_{t-1}^h}$ is aggregate asset price growth. For example, we can think of the borrowers as investors buying $\frac{L_t}{p_{t-1}^h}$ units of real estate at the start of the period, then they sell those units at the end of the period receiving as proceeds those units times the current real estate price (p_t^h). The term ω^α captures the idiosyncratic characteristics of the project or investor. This implies that for the same level of price growth ($\frac{p_t^h}{p_{t-1}^h}$) and investment (L_t), some investors are more profitable than others.

I assume that ω is distributed following a Pareto distribution with support $[M, \infty)$ and distribution function $G(\omega) = 1 - (\frac{M}{\omega})^\mu$, where $\mu > 0$ is the shape parameter. As μ increases, the dispersion of ω decreases and is increasingly concentrated towards the lower bound M . The Pareto assumption fits quite well firm-level data about the size

and productivity distribution of firms (Ghironi and Melitz 2005) as well as households' wealth distribution.

I assume that each bank randomly meets one borrower, observes the borrower's idiosyncratic type ω , and chooses lending standards to weed out the bad ones. To avoid modeling competition between banks, I assume that borrowers cannot shop around at different banks. I denote by $\pi_t \in [0, \infty)$ the bank's lending standards. A bank with lending standards π_t denies credit to any borrower with $\omega < M + \pi_t$, where M is the lower bound of the Pareto distribution of ω . Figure 3.1 plots the distribution of ω and the lending standards cutoff. Only borrowers to the right of $M + \pi_t$ receive credit. As π_t increases, lending standards are higher and the bank is more selective when lending because the bank has increased the minimum cutoff to give credit.

Higher lending standards also imply that it is less likely the bank will meet with a borrower worthy of receiving credit, because the probability $\Pr(\omega > M + \pi_t)$ is decreasing in π_t (holding everything else constant). Moreover, I assume that implementing higher lending standards is more costly than having lax standards (for example, due to increases in loan officers' time and the costs of analyzing the borrower and her project). I assume that the cost of implementing lending standards π_t when lending L_t is $C(\pi_t)L_t$. In the calibrated model I work with the function

$$C(\pi_t) = \xi\pi_t \tag{3.2}$$

where ξ is a parameter.

I make some assumptions to avoid equilibria in which bad borrowers who know they would not qualify for credit (they have $\omega < M + \pi_t$) do not apply for credit, causing banks to not need to spend resources on implementing standards. Ruckes (2004) discusses different assumptions that give the same result. For example,

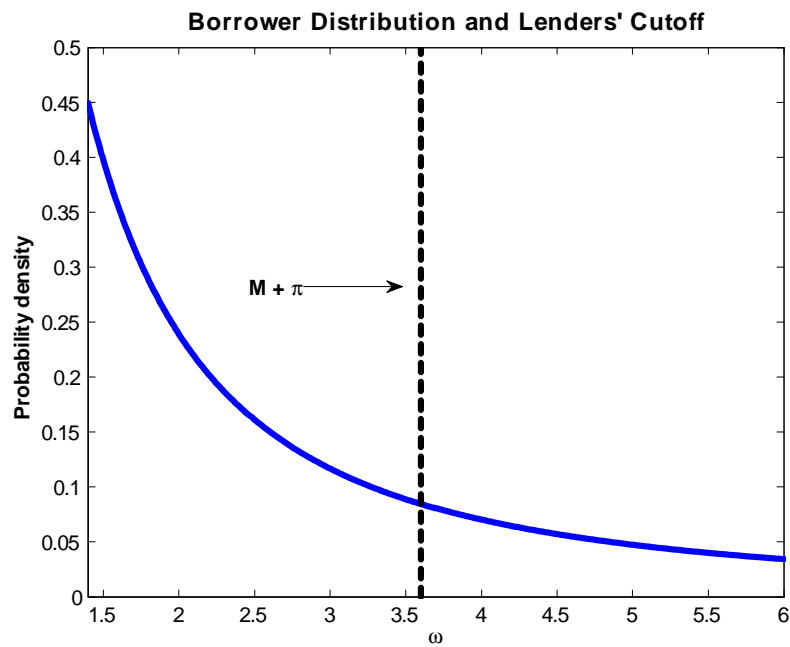


Figure 3.1: **Distribution of Borrowers and Lending Standards.** This picture plots the Pareto distribution of borrowers' idiosyncratic characteristics (ω) and how lending standards ($M + \pi$) are modeled as a cut-off such that no borrower below it qualifies for credit.

assuming borrowers do not know their types is equivalent to assuming good borrowers cannot signal their types and every borrower applies for credit because she obtains a non-verifiable control rent. Either of those assumptions, together with assuming that borrowers do not have any initial capital and cannot save, implies that borrowers always apply for the maximum credit.

To focus on the quantity of credit instead of on the price of credit, I assume that a fraction $\kappa \geq 0$ of the project's output, $y(\omega, \frac{p_t^h}{p_{t-1}^h}, L_t)$, goes to the borrower and the remaining fraction, $(1 - \kappa)$, goes to the lender. Thus, I am assuming state contingent payoffs to the lender. This can be justified if we think of the lenders as banks using debt contracts including many covenants that make the contract state contingent. I could also think of them as large banks or non-bank financial intermediaries investing through ways other than standard debt contracts. Boot and Thakor (2010) document large increases in financial intermediation through equity instruments. Several recent models of banks, such as Bocola (2013), Gertler and Kiyotaki (2010) or Dedola et al. (2013), also use equity contracts for simplicity. This assumption does not alter my results. The two frictions that I study would also lead to inefficient lending standards if payoffs to the lender were the same as those in a standard debt contract, that is, only state contingent in case of borrower's default.⁷

3.3.2 IMPERFECT INFORMATION

Asset price growth $\left(\frac{p_t^h}{p_{t-1}^h}\right)$ is exogenous and stochastic. It is unknown at the time of decision-making in period t , but is observed at the end of the period. To capture imperfect information, I assume that $\left(\frac{p_t^h}{p_{t-1}^h}\right)$ is the sum of two unobservable parts,

⁷This result is available in an Appendix upon request.

both with permanent effects, but one part is persistent while the other is not:

$$\frac{p_t^h}{p_{t-1}^h} = \exp(z_t + \eta_t) \quad (3.3)$$

where z_t is the persistent part that follows a two state Markov chain. That is, prices can have high or low growth $z_t = \{z^L, z^H\}$, with $z^L < z^H$, and transition matrix

$$P = \begin{bmatrix} P_{LL} & P_{LH} \\ P_{HL} & P_{HH} \end{bmatrix}$$

The non-persistent part η_t is an *i.i.d.* Normal shock with mean $-\frac{\sigma_\eta^2}{2}$ and variance σ_η^2 . This assumption for the mean of η_t ensures that, conditional on z_t , $\frac{p_t^h}{p_{t-1}^h}$ follows a lognormal distribution whose conditional mean is $\exp(z_t)$. I will refer to the η_t shock as a noise shock because it prevents banks from perfectly observing z_t and it is a shock to which agents should not react because it is *i.i.d.*

Banks must make period t decisions before price growth is known, so they form expectations about it from their past observations (I denote by Θ_{t-1} the information set known at the start of the t period). They do so by forecasting the unobservable state of the persistent part, z_t , from past observations of $\frac{p_t^h}{p_{t-1}^h}$ using a Bayesian filter. I denote by $p_{t-1} \equiv \Pr(z_t = z^H | \Theta_{t-1})$ the belief or prior of z_t being in the high state in period t .

Banks start period t with a prior p_{t-1} and base their period t decisions on this prior. Once $\frac{p_t^h}{p_{t-1}^h}$ is observed at the end of period t , agents compute their posterior beliefs about the state of the persistent component, $\Pr(z_t = z^i | \Theta_t)$, using the Bayesian filter

$$\Pr(z_t = z^i | \Theta_t) = \frac{f\left(\frac{p_t^h}{p_{t-1}^h} | z_t = z^i\right) \Pr(z_t = z^i | \Theta_{t-1})}{f\left(\frac{p_t^h}{p_{t-1}^h} | z_t = z^j\right) \Pr(z_t = z^j | \Theta_{t-1}) + f\left(\frac{p_t^h}{p_{t-1}^h} | z_t = z^i\right) \Pr(z_t = z^i | \Theta_{t-1})}, \quad i = H, L \quad (3.4)$$

where the conditional density $f(\frac{p_t^h}{p_{t-1}^h}|z_t = z^i)$ is the normal probability density

$$f\left(\frac{p_t^h}{p_{t-1}^h}|z_t = z^i\right) = \frac{1}{\sigma_\eta \sqrt{2\pi}} \exp\left(-\frac{1}{2\sigma_\eta^2} \left(\frac{p_t^h}{p_{t-1}^h} - z^i + \frac{\sigma_\eta^2}{2}\right)^2\right), \quad i = H, L \quad (3.5)$$

Banks form next period's prior p_t by updating the posterior with the transition matrix P

$$p_t = \Pr(z_{t+1} = z^H|\Theta_t) = \Pr(z_t = z^H|\Theta_t)P_{HH} + \Pr(z_t = z^L|\Theta_t)P_{LH} \quad (3.6)$$

This is the prior used to make decisions in period $t + 1$.

I will use the notation $E_{t-1}(\cdot)$ to denote the expectation over $\frac{p_t^h}{p_{t-1}^h}$ conditional on the information known at the start of the period. That is, the expectation of the proceeds from the project conditional on information at the start of period t is:

$$\begin{aligned} E_{t-1}\left[y\left(\omega, \frac{p_t^h}{p_{t-1}^h}, L_t\right)\right] &= E_{t-1}\left[\frac{p_t^h}{p_{t-1}^h}\right] \omega^\alpha L_t = \\ &= [p_{t-1}(\exp(z^H)) + (1 - p_{t-1})(\exp(z^L))] \omega^\alpha L_t \end{aligned} \quad (3.7)$$

3.3.3 BANKS

In every period t there is a continuum of mass one of risk neutral banks. Banks can fund their loans with their own equity, K_t , whose gross cost I assume to be R_t^E , or with deposits or borrowings, B_t , that cost R_t^B . Banks are subject to a capital requirement, $\gamma \geq 0$, such that

$$L_t \leq B_t + K_t \quad (3.8)$$

$$K_t \geq \gamma L_t \quad (3.9)$$

I assume that

$$R_t^E \geq R_t^B. \quad (3.10)$$

That is, the cost of equity is larger than the cost of debt, for example because equity holders face the risk of losing their investment while the debtholders are deposit insured or the government provides a guarantee. This assumption is important because as the capital requirement increases, banks' cost of funds increases as well, since banks are financing a larger share of their loans with equity.⁸

Each bank lives for one period, meets one borrower and chooses its lending standards π_t . If the borrower does not satisfy the lending standards ($\omega < M + \pi_t$), then the bank does not lend and sits on its capital. If the borrower satisfies the standards ($\omega \geq M + \pi_t$) then the bank lends the amount L_t . At the end of the period $\frac{p_t^h}{p_{t-1}^h}$ is realized, the return from the project is observed, split between the bank and its borrower, and the borrower and the bank separate. With the proceeds received, the bank pays its debtholders and the cost of implementing lending standards. Any remaining proceeds then go to shareholders. Limited liability implies the net profits can never be negative, as shareholders are not asked to inject more capital to cover losses. The payoff for the bank from lending is

$$\left((1 - \kappa)y\left(\omega, \frac{p_t^h}{p_{t-1}^h}, L_t\right) - R_t^B B_t - C(\pi_t) L_t \right)^+$$

where the notation $(x)^+$ stands for the maximum operator, $\max(x, 0)$.

For a given K_t and p_{t-1} the bank chooses lending standards to maximize expected shareholders' value at the end of the period. Since lending is risky, I assume that profits from the risky activity are discounted using the cost of equity while those from not taking risk are discounted at the deposit rate. The banks take expectations over both ω (because the bank does not know which type of borrower it will meet)

⁸As discussed by Admati et al. (2013), it may be that higher capital requirements lower the cost of equity. Our set up is a partial equilibrium model and cannot capture that effect. This should not invalidate our analysis if the cost of bank equity remains higher than the cost of raising debt or deposits for banks, which would probably be the case if the deposits are insured while equity is more risky.

and $\frac{p_t^h}{p_{t-1}^h}$. Banks start period t with a prior, p_{t-1} , inherited from the posterior of the previous cohort of bankers according to equation (3.6). The bank solves:

$$\max_{\{\pi_t, L_t\}_0^\infty} \int_M^{M+\pi_t} \frac{1}{R_t^B} K_t dG(\omega) + E_{t-1} \left(\int_{M+\pi_t}^\infty \frac{1}{R_t^E} \left((1-\kappa)y\left(\omega, \frac{p_t^h}{p_{t-1}^h}, L_t\right) - R_t^B B_t - C(\pi_t) L_t \right)^+ \right) dG(\omega) \quad (3.11)$$

s.t. (3.8) and (3.9)

where $[M, M + \pi_t]$ is the region where the banks are not lending ($L_t = 0$).⁹

Given banks' linear utility, if the borrower is considered worthy of receiving credit, the bank will always try to give her the maximum credit possible. Thus, equations (3.8) and (3.9) would hold with equality. However, given that not all banks are giving credit, even for linear utility banks, the model can match the empirical fact that the banking system holds capital above the regulatory minimum, a fact discussed by Allen et al. (2011) among others.

I denote by $P(\omega, \frac{p_t^h}{p_{t-1}^h}, K_t, \pi_t)$ the net profits at the end of the period for a bank with capital K_t and lending standards π_t , matched with a borrower of type ω when asset price growth is $\frac{p_t^h}{p_{t-1}^h}$

$$P\left(\omega, \frac{p_t^h}{p_{t-1}^h}, K_t, \pi_t\right) = \left\{ \begin{array}{l} \left((1-\kappa)y\left(\omega, \frac{p_t^h}{p_{t-1}^h}, L_t\right) - R_t^B B_t - C(\pi_t) L_t \right)^+ \text{ if } \omega \geq M + \pi_t \\ K_t \text{ if } \omega < M + \pi_t \end{array} \right\} \quad (3.12)$$

I assume that at the end of each period, banks' net cash flows are aggregated to form next period's aggregate capital K_{t+1} , which will be evenly split among the next

⁹To ensure the objective function is finite, I require that $\alpha < \mu$.

cohort of banks.¹⁰

$$K_{t+1} = \int_M^\infty P(\omega, \frac{p_t^h}{p_{t-1}^h}, K_t, \pi_t) dG(\omega) \quad (3.13)$$

3.4 THE LENDING STANDARDS DECISION

The bank chooses its lending standards, π_t , by solving equation (3.11), where the notation $(x)^+$ stands for the maximum operator, $\max(x, 0)$. The bank's problem can thus be broken into two separate cases, one in which the bank lends to borrower types that are expected to default ($\max(x, 0) = 0$) and one in which the bank does not lend to borrower types that are expected to default ($\max(x, 0) = x$). I define the objective function for the bank when there is expected default as:

$$W(\pi_t) = \int_M^{M+\pi_t} \frac{1}{R_t^B} K_t dG(\omega) + E_{t-1} \left(\int_{\widehat{\omega}(\pi_t)}^\infty \frac{1}{R_t^E} (1 - \kappa) y(\omega, \frac{p_t^h}{p_{t-1}^h}, L_t) - R_t^B B_t - C(\pi_t) L_t \right) dG(\omega) \quad (3.14)$$

where $\widehat{\omega}(\pi_t) \geq M + \pi_t$ is the threshold borrower expected to generate a lending payoff for the bank of zero. That is, $\widehat{\omega}(\pi_t)$ satisfies:

$$(1 - \kappa) E_{t-1} \left[\frac{p_t^h}{p_{t-1}^h} \right] (\widehat{\omega}(\pi_t))^\alpha L_t - R_t^B B_t - C(\pi_t) L_t = 0 \quad (3.15)$$

Likewise, I define the objective function for the bank when there is no expected default as:

$$V(\pi_t) = \int_M^{M+\pi_t} \frac{1}{R_t^B} K_t dG(\omega) + E_{t-1} \left(\int_{M+\pi_t}^\infty \frac{1}{R_t^E} (1 - \kappa) y(\omega, \frac{p_t^h}{p_{t-1}^h}, L_t) - R_t^B B_t - C(\pi_t) L_t \right) dG(\omega). \quad (3.16)$$

¹⁰This assumption is without loss of generality since it is the leverage ratio $\left(\frac{K_t}{L_t}\right)$ and not the level of capital that affects the choice of lending standards, as the bank's objective function is linear in capital, K_t . Thus, in this model small banks and large banks behave in the same way if they have the same leverage ratio.

where, implicitly, $M + \pi_t > \widehat{\omega}(\pi_t)$. The optimal choice of lending standards in each of these cases can be defined as follows:

$$\pi_t^* = \arg \max_{\pi_t} W(\pi_t) \quad (3.17)$$

and

$$\pi_t^{**} = \arg \max_{\pi_t} V(\pi_t). \quad (3.18)$$

When there is lending with expected default, the following first-order condition implicitly defines π_t^* as long as $\widehat{\omega}(\pi_t^*) \geq (M + \pi_t^*)$:

$$\frac{1}{R_t^E} \left(\frac{1}{\gamma} \right) C'(\pi_t^*) M^\mu (\widehat{\omega}(\pi_t^*))^{-\mu} = \frac{1}{R_t^B} \mu M^\mu (M + \pi_t^*)^{-\mu-1}. \quad (3.19)$$

This condition equates the discounted marginal revenue from lending to types above $\widehat{\omega}(\pi_t^*)$ (the left-hand side of equation 3.19) with the discounted marginal opportunity cost from lending to the cutoff type, $M + \pi_t$ (the right-hand side of equation 3.19). There are two important relationships that can be observed in this optimality condition. First, because the marginal benefit of lending falls as the capital requirement rises, a higher capital requirement causes banks to want to lend less. Hence they raise their lending standards to lend to fewer borrowers. Second, as banks' beliefs about real estate price growth deteriorate, banks will want to seek out higher quality borrowers and will raise their lending standards in response.

For the case of lending without expected default, the first-order condition that implicitly defines π_t^{**} is:

$$\frac{1}{R_t^E} \left(\frac{1}{\gamma} \right) \left[(1 - \kappa) E_{t-1} \left[\frac{p_t^h}{p_{t-1}^h} \right] (M + \pi_t^{**})^\alpha - R_t^B (1 - \gamma) - C(\pi_t^{**}) + \left(\frac{1}{\mu} \right) (M + \pi_t^{**}) C'(\pi_t^{**}) \right] = \frac{1}{R_t^B}. \quad (3.20)$$

as long as $(M + \pi_t^{**}) > \widehat{\omega}(\pi_t^{**})$. In this case, the first-order condition equates the discounted marginal revenue from lending to the cutoff type $M + \pi_t^{**}$ (the left-hand

side of equation 3.20) with the discounted opportunity cost from lending to the cutoff type (the right-hand side of equation 3.20). Again, we see that the marginal benefit of lending falls as the capital requirement rises, implying banks will want to raise their standards to lend to fewer borrowers. Also, more pessimistic beliefs about real estate price growth will again lead to banks to raise their lending standards.

Banks choose the level of lending standards that maximizes value over these two cases. That is, they will choose π_t such that:

$$\pi_t = \arg \max_{\{\pi_t^*, \pi_t^{**}\}} \{W(\pi_t^*), V(\pi_t^{**})\}. \quad (3.21)$$

Lending with expected default ($\pi_t = \pi_t^*$) is costly as banks lose equity on the defaulted borrowers. Banks will only choose to do so if the marginal costs of implementing standards such that $\pi_t = \pi_t^{**}$ are too high.

3.5 QUANTITATIVE PROPERTIES

In this section I first calibrate the model to match long-term averages of real estate prices and financial data series. Then, I use recent data on credit booms and busts to illustrate how imperfect information can generate rational credit booms and busts in the model. Appendix B contains the model counterparts to the data facts. It also discusses the numerical algorithm.

3.5.1 CALIBRATION

I calibrate one period in the model to be one year and set the exogenous cost of debt, R_t^B , to 2% which is the standard risk free rate in most macroeconomic calibrations. I set the cost of bank equity, R_t^E , to 7% following Damodaran (2012). I assume a capital requirement γ of 4%, which was the Tier 1 capital requirement under Basel I.

I follow Ceron and Suarez (2006) to parameterize the stochastic process of equation (3.3). They use Hamilton (1989) methodology to estimate a two-state Markov switching process for housing prices using inflation-adjusted residential property price index data from fourteen developed countries. I use their estimates for P_{LL} , P_{HH} and for the ratio between the good and the bad persistent state, $\frac{1+z^H}{1+z^L}$. This ratio pins down z^L once I set z^H , which becomes the scale parameter for the real estate price shock and is selected as explained below.

I select the remaining seven parameters (borrowers' fraction of output κ , borrowers' technology α , screening cost function ξ , the real estate price shock in the high state z^H , the volatility of the i.i.d shock σ_η , and the parameters of borrowers' distribution M and μ) for the model to jointly match the following facts for 1985-2006: 1) Average fraction of reserves held in U.S. banks' asset portfolios (6.1%) (series: CASACBM027SBOG and TLAACBM027SBOG from the FRED database); 2) Average real return on equity (13.1%) for U.S. banks (series: USROE from the FRED database); 3) Average real return on assets (1.1%) for U.S. banks (series: USROA from the FRED database); 4) Delinquency rate to match the historical default rates computed by Moody's (8.1%) for B/B borrowers, which is the rating for the majority of defaulting borrowers one year before default (Moody's 2002); 5) Average credit-to-GDP ratio (81.1%) for Ireland, Spain, the U.K. and the U.S. from Beck et al. (2009), which I proxy by the ratio of borrower credit to borrower output in the model; 6 and 7) A 5% likelihood of noise shocks implying losses larger than 82% of bank capital. This last fact is based on the estimation by the Basel Committee on Banking Supervision (2010b) that there is a 5% probability of a member country facing a crisis in a given year, and that the last two U.S. financial crises (the Savings and Loan Crisis of 1988 and the recent crisis) cost regulators on average 82% of banks'

Table 3.1: Parameters

$M = 1.4$	$\mu = 1.3$	$\alpha = 0.1$
$\kappa = 0.116$	$P_{HH} = 0.96$	$P_{LL} = 0.97$
$\gamma = 0.04$	$\xi = 0.03$	$K_0 = 1$
$z^H = 0.0488$	$z^L = -0.0231$	$\sigma_\eta = 0.036$
$R_t^B = 1.02$	$R_t^E = 1.07$ for all t	
Note: For calibration details see Section 3.5.1		

Table 3.2: Calibration

	Data	Model
1) Reserves as fraction of banks' asset portfolios	6.1%	5.8%
2) ROE	13.1%	13.2%
3) ROA	1.1%	1.3%
4) Delinquency rate	8.1%	7.7%
5) Credit-to-output ratio	81.1%	82.1%
6) Probability of crisis	5%	5%
7) Losses during crisis (as a % of banks' capital)	82%	86%
Note: For calibration details see Section 3.5.1		

capital, which I discuss further in Section 3.7. Table 3.1 contains the parameters that I obtain, and Table 3.2 reports how well the model matches the targets.

The calibration implies a real estate price growth rate of 5% if the persistent component of price growth is high and a -2% growth rate if it is low. Likewise, the invariant distribution of the calibrated Markov transition matrix P implies that in the long-run, the persistent component of price growth is high 40% of the time low 60% of the time.

Figure 3.2 illustrates how banks update their beliefs given the calibration. It plots how, for a given prior, observations of price growth lead to new posteriors.¹¹ Three facts are interesting. First, posterior beliefs are increasing in the asset price growth rate. That is, when banks see a higher price growth rate, they attribute part of it to a higher likelihood that the persistent state of price growth is z^H . In other words, they always attribute part of the growth to fundamentals. Second, a larger number of low posterior beliefs arise when the prior itself is also low. Similarly, I observe a larger number of high posterior beliefs when the prior itself is also high. That is, given the calibration, banks need to see large changes in price growth in order to drastically update their beliefs. Third, it is possible, given different priors, that different observations of house price growth can lead to the same posterior belief.

Figure 3.3 shows why beliefs matter. It plots banks' lending standards and total credit for different levels of the prior p_{t-1} . Optimism leads to more credit.

3.5.2 RATIONAL CREDIT BOOMS AND BUSTS

In this section, I show that a model with imperfect information can generate boom-bust patterns. Moreover, I test the ability of the calibrated model to match data. Elekdag and Wu (2011) study data from 1960-2010 and identify 99 credit booms across 21 advanced and 43 emerging economies.¹² Figure 3.4A shows the typical evolution of these booms over five-year windows centered at their peaks. The figure distinguishes between different kinds of booms (worst booms, abrupt booms and smooth booms) depending on how severe the following crises were.

¹¹It presents a scatter plot of the transition of beliefs for a time series of 10,000 periods. The time series starts with z_t at its long-run mean and with banks' prior p_t consistent with that mean.

¹²A credit boom is defined as an episode when the cyclical component of real credit is larger than 1.55 times its standard deviation.

Transition of Beliefs for Different Observations of House Price Growth

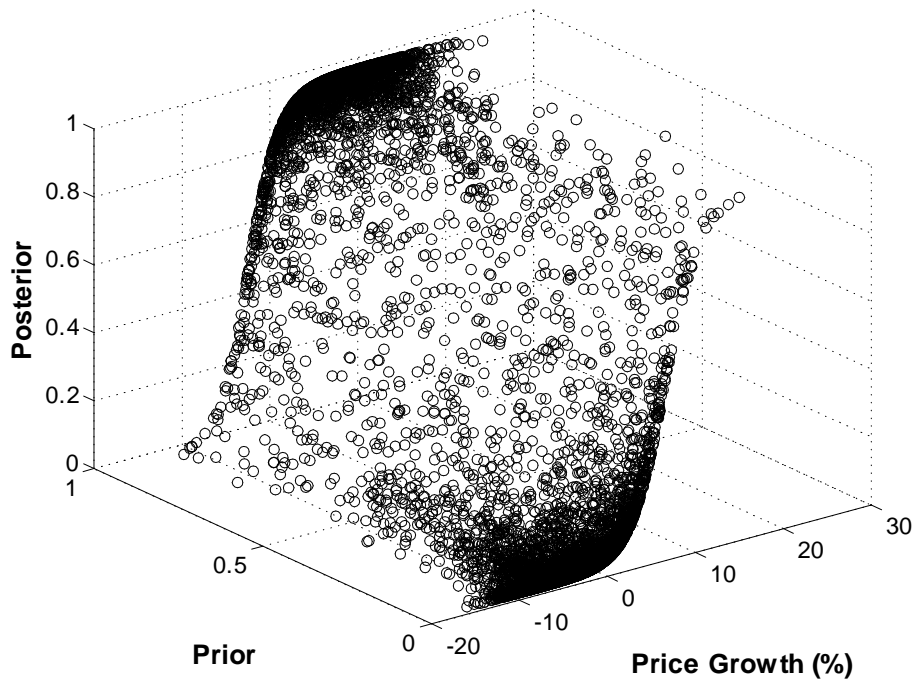


Figure 3.2: **Transition of Beliefs for Different Observations of House Price Growth.** This figure plots banks' posterior belief about being in the high state of the economy as a function of banks' prior and different observations of house price growth. The data come from simulating the stochastic process described in Section 3.3.2 for 10,000 periods.

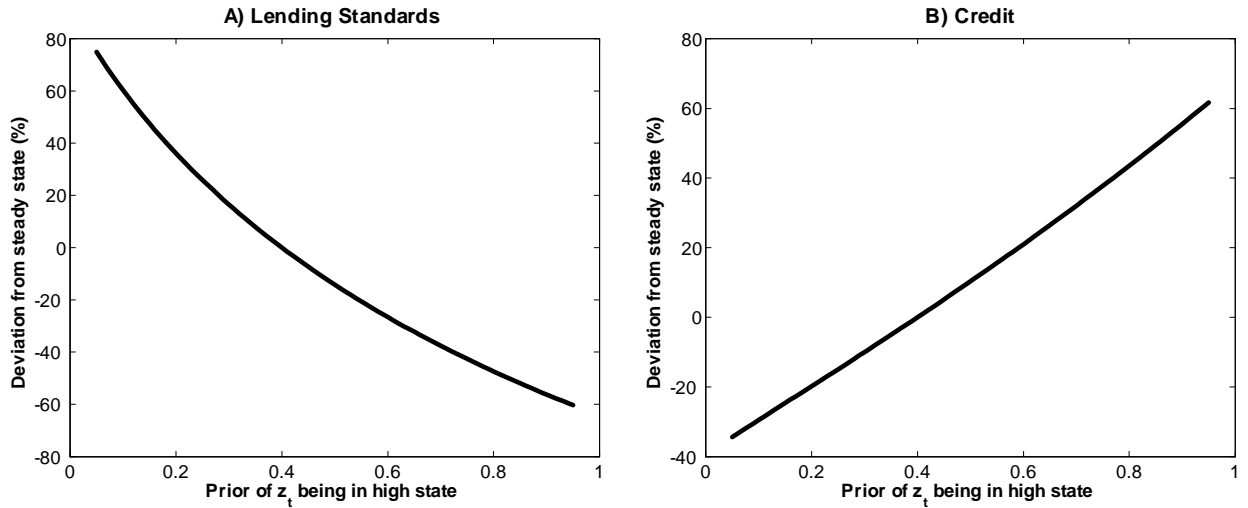


Figure 3.3: **Countercyclical Lending Standards and Procyclical Credit.** This Figure plots lending standards and credit as a function of the prior about the persistent part of price growth, z_t .

I ask what would happen in the model if I input a pattern of house price growth, $\left\{ \frac{p_t^h}{p_{t-1}^h} \right\}$, driven by noise shocks η_t that allows the model to generate a credit boom matching the data reported in Figure 3.4A. When $\left\{ \frac{p_t^h}{p_{t-1}^h} \right\}$ increases, then banks' beliefs rise (Figure 3.4C) and lending standards fall as shown in Figure 3.4D. This leads to the credit increases observed in Figure 3.4A. Return on assets in Figure 3.4E is initially high because banks are lending more and the noise shocks η_t are positive. However, when the noise shocks disappear, the fraction of non-performing loans rises (Figure 3.4F), bank profits fall (Figure 3.4E), and banks suddenly readjust expectations about the persistent part of the aggregate component of income (Figure 3.4C). The combination of banks tightening their lending standards and bank losses lowering banks' available capital leads to a severe contraction in credit, generating a bust.

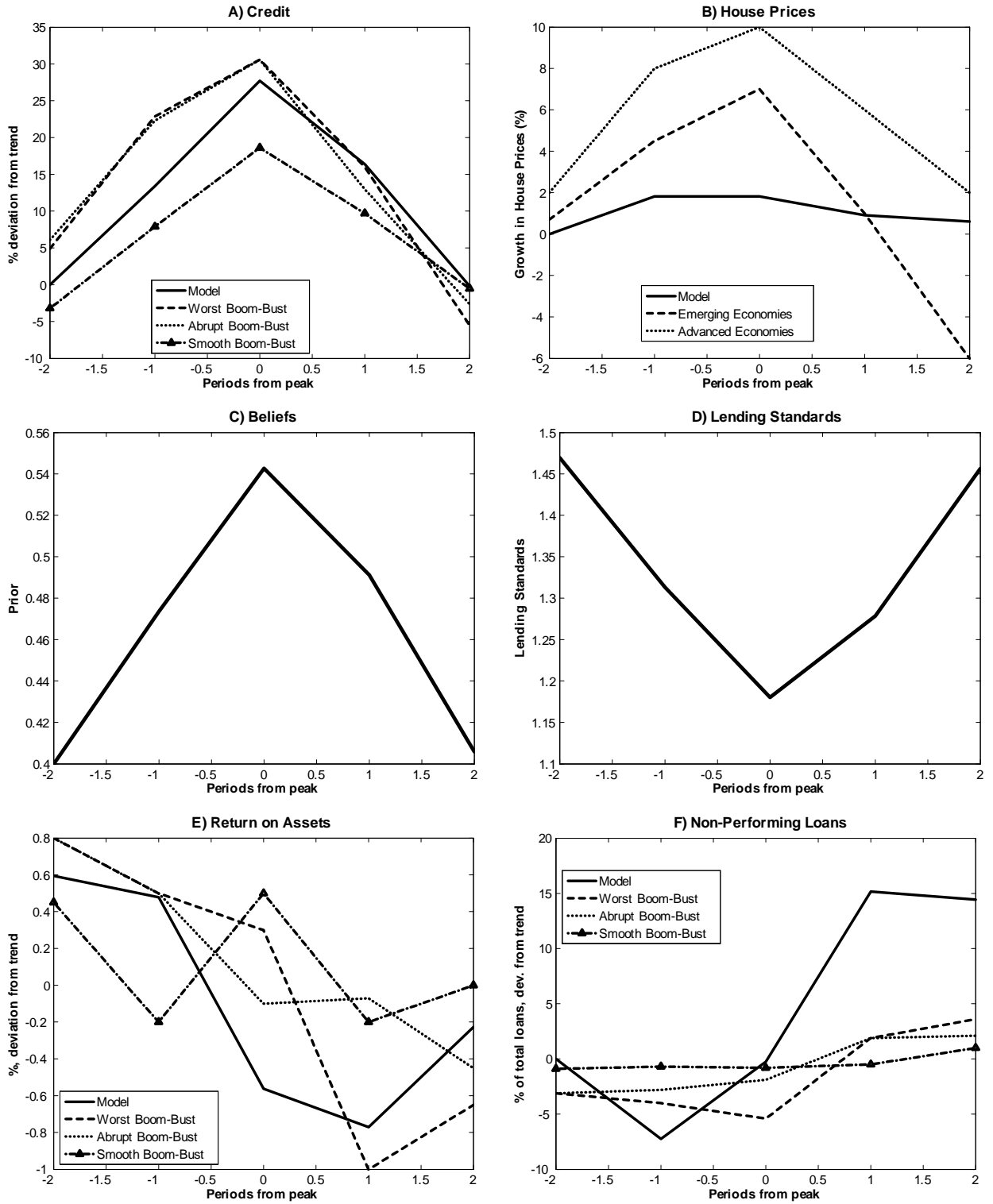


Figure 3.4: **Credit Booms in the Model and in the Data.** This Figure plots empirical patterns documented by Elekdag and Wu (2011) and a model-simulated credit boom-bust. The numerical algorithm is discussed in Appendix B.2.

Interestingly, the model predictions seem to be in line with the data. This serves as motivation to use the model for the policy applications of the next sections.

3.6 EARLY WARNING INDICATORS

Implementation of the Basel III countercyclical capital buffer requires national regulators to identify data-based early-warning indicators of excessive credit growth. In this section, I use the model framework to investigate which patterns of banks' beliefs and real estate price growth may induce damaging credit booms. I measure risk by the size of losses in excess of bank capital and by the likelihood of such losses. Interestingly, I find that with rational agents the more dangerous patterns are not those of maximum optimism, even if standards are monotonically decreasing in optimism.

For a given realization of price growth, $\frac{p_t^h}{p_{t-1}^h}$, and banks' lending standards, π_t , I can define the function $\tilde{\omega}\left(\frac{p_t^h}{p_{t-1}^h}, \pi_t\right)$ as the borrower type receiving credit such that bank capital is just returned. That is, $\tilde{\omega}\left(\frac{p_t^h}{p_{t-1}^h}, \pi_t\right)$ is the borrower type such that

$$(1 - \kappa)y\left(\tilde{\omega}, \frac{p_t^h}{p_{t-1}^h}, L_t\right) - R_t^B B_t - C(\pi_t) L_t - K_t = 0$$

or

$$\tilde{\omega}\left(\frac{p_t^h}{p_{t-1}^h}, \pi_t\right) = \left[\frac{\gamma + R_t^B (1 - \gamma) + C(\pi_t)}{(1 - \kappa) \left(\frac{p_t^h}{p_{t-1}^h}\right)} \right]^{1/\alpha}. \quad (3.22)$$

Banks make losses in excess of their capital for all financed borrowers whose idiosyncratic component of income ω was lower than $\tilde{\omega}\left(\frac{p_t^h}{p_{t-1}^h}, \pi_t\right)$, thus the losses of the banking system in excess of bank capital are the sum of the losses on all financed borrowers ($\omega > M + \pi_t$) whose type is below $\tilde{\omega}\left(\frac{p_t^h}{p_{t-1}^h}, \pi_t\right)$. I define those banking system

losses as

$$\Omega_t = - \int_{M+\pi_t}^{\tilde{\omega}\left(\frac{p_t^h}{p_{t-1}^h}, \pi_t\right)} \left[(1 - \kappa)y(\omega, \frac{p_t^h}{p_{t-1}^h}, L_t) - R_t^B B_t - C(\pi_t) L_t - K_t \right] dG(\omega) \quad (3.23)$$

where I multiply by a negative sign to have a positive value for the losses.

The size of bank losses depends on both how bad the price growth shock is, $\frac{p_t^h}{p_{t-1}^h}$, and on banks' lending standards, π_t . From Figure 3.3 we know that lending standards are a decreasing function of beliefs. In Figure 3.5 I plot the probability of observing losses (Ω_t) in excess of bank capital of different sizes for different prior beliefs. Specifically, I set Ω_t to 50%, 65%, 75%, or 100% of banks' beginning-of-period capital, compute the corresponding s^* that is the size of the aggregate shock bad enough to generate such losses, and then plot the probability of observing a shock worse than s^* at each level of the prior.

In each of the four panels of Figure 3.5, we see that the probability of banking system losses is mostly increasing in the prior, illustrating that the likelihood of observing a crisis rises with bank optimism, as lending standards are decreasing in bank optimism (Figure 3.3) and there is more lending. However, the probabilities are non-monotonic in the prior, p_t , because for very high beliefs, even if the banks have very low lending standards, it is very unlikely to see a shock bad enough to generate 50%, 65%, 75%, or 100% bank losses.

Thus, the non-monotonicity illustrates two forces affecting the regulator's potential losses: as p_t increases banks are more exposed to risks because their standards are lower, but these risks are also smaller because rational banks have larger p_t when it is less likely that a bad shock happens. Over most of the p_t range, more optimism means more risk for the regulator. In other words, the more dangerous times are times of optimism where there are doubts about the strength of the fundamentals.

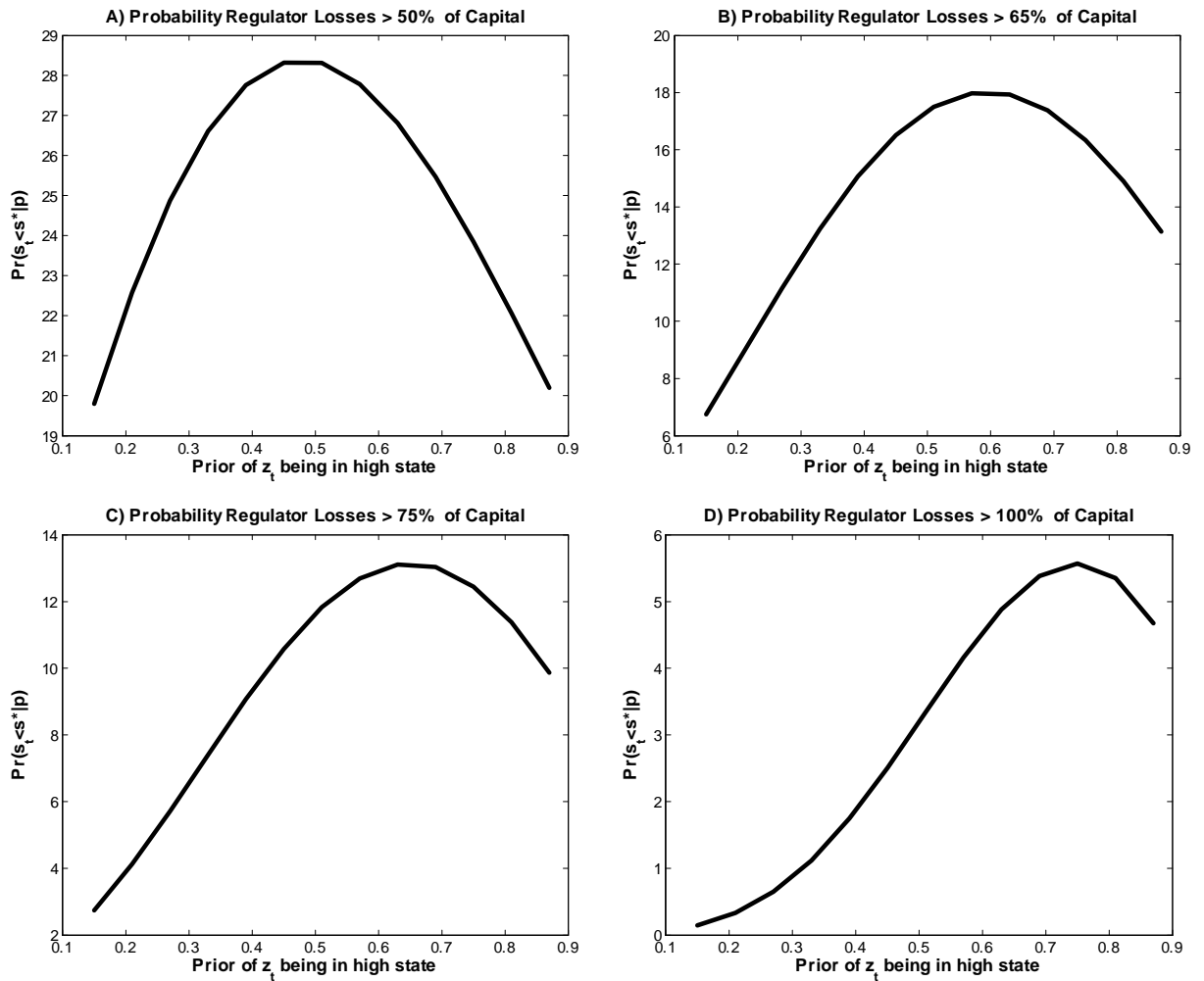


Figure 3.5: Banks' Beliefs and Probability of Regulator Losses. This figure plots the probability that the regulator experiences losses of at least 50%, 65%, 75%, or 100% of banking system capital as a function of the prior about the persistent component of house price growth.

Now that I have examined how the risk of regulator losses changes with the prior, I turn to how the risk responds to different sequences of real estate price growth. In Figure 3.6, I plot how the size of regulator losses changes for three scenarios of real estate price growth: a sequence of two periods of 2%, 5% and 8% growth respectively. I specifically examine the size of regulator losses that occur with 2% probability. In all three scenarios, the starting house price growth rate is at the mean of the invariant distribution of the stochastic process in equation (3.3) and banks have the prior p_t consistent with that mean.

In Panel A, I find that real estate price growth around 2% generates an increasing risk of regulator losses. This level of real estate price growth causes banks to slowly update their beliefs and take on more risk. Panels B and C, however, show that the pattern of risk is non-monotonic. The size of potential losses is highest once the first real estate price growth shock is observed. At faster rates of real estate price growth, banks update their beliefs relatively quickly. Hence, more risk arises in the banking system after the initial shock. However, upon observing the second shock, it is increasingly likely that the housing market is actually in the high growth state and less likely it will see a housing price growth shock bad enough to generate large losses, so risk falls in the second period. That is, as in the previous figure, there is a trade-off between the risk generated by laxer lending standards associated with higher growth, and the fact that if the growth is very high, then it is very unlikely not to come from good fundamentals. Weighting these two channels gives as a result that the sequence of 5% real estate price growth (Panel B) induces the most risk.

Figure 3.7 redoes Figure 3.6 but focuses on the probability of a crisis (defined as regulator losses of 100% or more of bank capital) for the same three scenarios of real estate price growth. I observe patterns of regulator risk similar to those discussed in Figure 3.6. In Panel A, the probability of a crisis is increasing for real estate price

House Price Dynamics and Regulator Losses

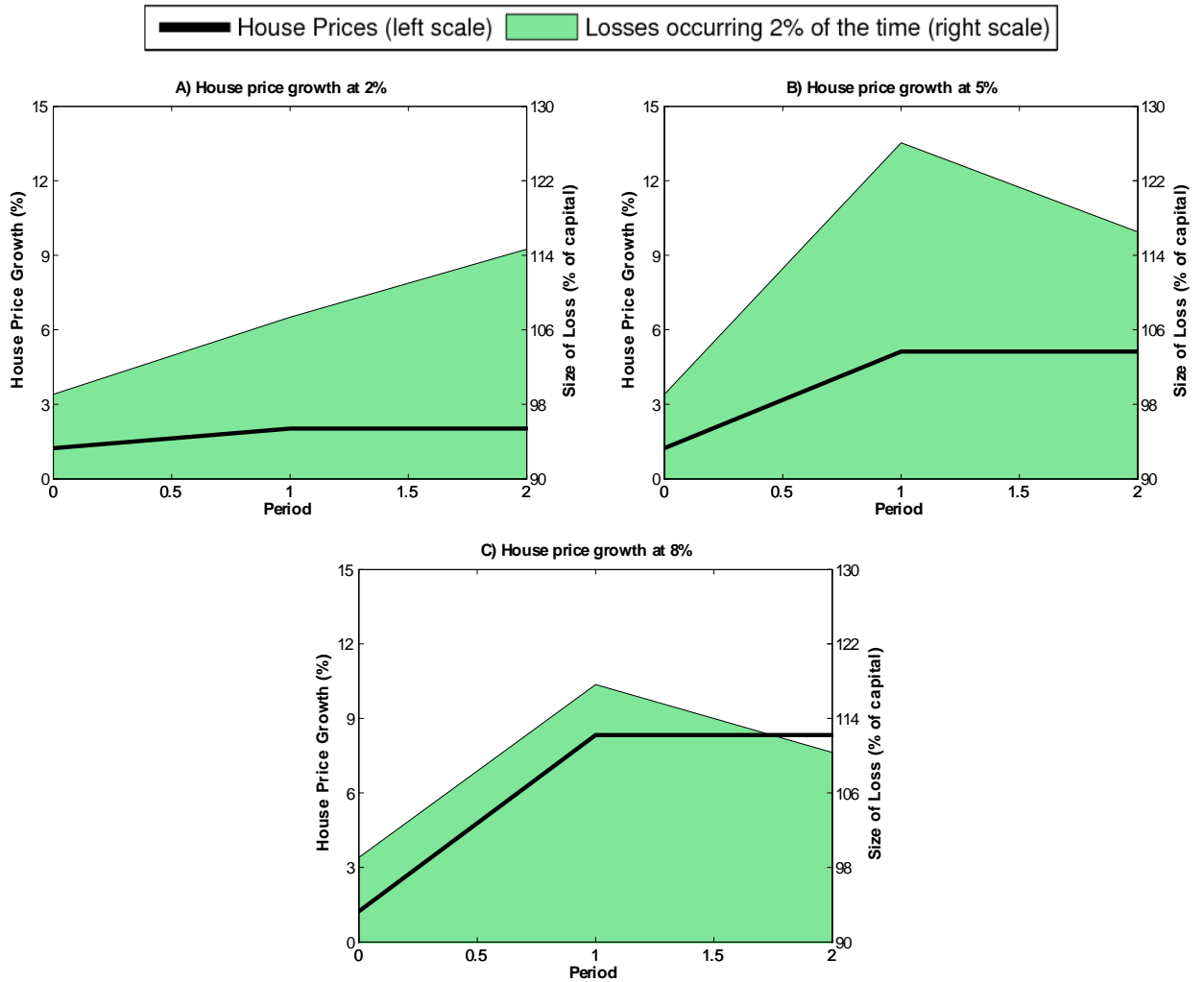


Figure 3.6: **House Price Dynamics and Regulator Losses.** This figure plots regulator losses as a percentage of banking system capital that occur 2% of the time for different house price growth rates.

growth around 2%, due to a gradual updating of bank beliefs. Panels B and C again display a non-monotone response to real estate price growth rates of 5% and 8% respectively. The risk of crisis is again at a maximum for the sequence of 5% real estate price growth (Panel B).

3.7 A VALUE-AT-RISK MACROPRUDENTIAL REGULATOR

In this Section I analyze a Value at Risk (VaR) framework to set capital requirements and leverage ratios.¹³ VaR is a tool commonly used to assess the risk of a portfolio. It measures the minimum potential loss of a portfolio for a given confidence interval. For example, a VaR of \$100 with a 98% confidence level means that there is a 2% chance the portfolio will lose more than \$100 over a specified period.

I propose that the regulator sets the capital requirement, γ , using a VaR criteria such that losses (Ω_t) in excess of $x\%$ or more of banking system capital occur with confidence level $1 - \rho$.¹⁴ That is, the regulator chooses the capital requirement such that

$$\Pr\left(\Omega_t > \left(\frac{x}{100}K_t\right) | p_t\right) = \rho. \quad (3.24)$$

Losses (Ω_t) are defined as in equation (3.23).¹⁵ The fact that banks are leveraged institutions implies that losses could exceed all banking capital.

¹³The Basel Committee seems to reason with a VaR framework. The Committee discussed that the goal of regulation is to reduce from 5% to 1%, 2% or 3% the probability that a country faces a crisis in any given year (Walter 2011).

¹⁴I motivate this assumption using the fact that regulators, via deposit insurance or government guarantees, often cover losses in excess of bank equity. Similarly, I could motivate it in the case of a regulator that does not like banks defaulting on their creditors.

¹⁵Laeven and Valencia (2012) estimate that the fiscal cost of the U.S. Savings and Loan crisis in 1988 was 3.7% of GDP and the cost of the recent U.S. crisis was around 4.5% of GDP. These costs include bank recapitalizations and other outlays related to restructuring the financial sector, but do not include asset purchases. Using that the ratio of equity to GDP in 1988 and 2008 was 3.5% and 7.7% respectively, I can convert the data on losses to a percentage of bank equity. I obtain that the fiscal costs of those crises were between 50% and 100% of bank capital. This is the range I will use for $x\%$.

House Price Dynamics and Probability of Crisis

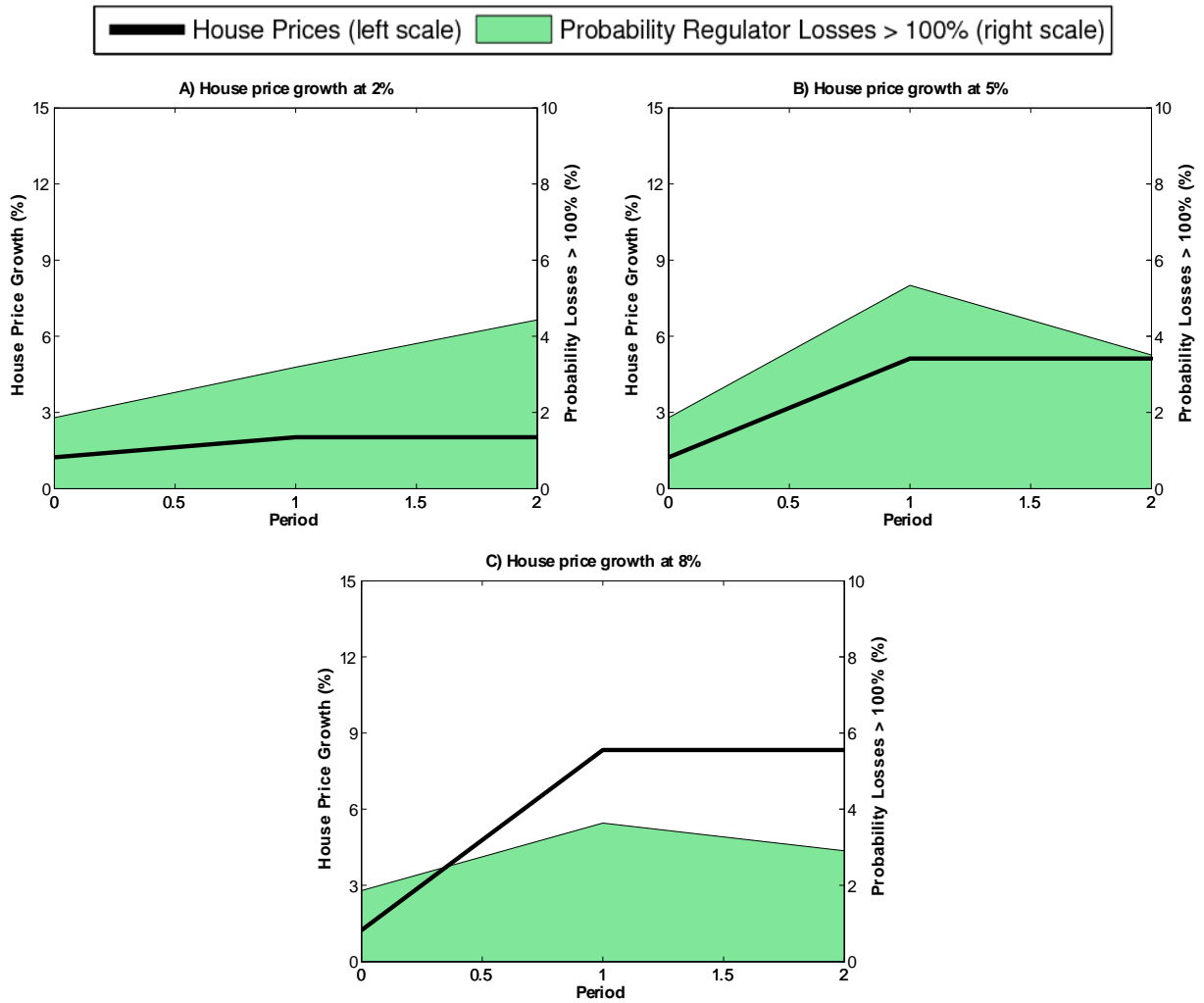


Figure 3.7: **House Price Dynamics and Probability of Crisis.** This figure plots the probability of regulator losses of 100% or more of banking system capital for different house price growth rates.

Table 3.3: Regulator Losses, the Capital Requirement and Value-at-Risk

Value-at-Risk Confidence Level:	98%	95%	90%
Capital Requirement	Regulator Losses		
4.0%	125%	103%	83%
4.5%	105%	86%	69%
5.0%	90%	74%	59%
5.5%	80%	66%	52%
6.0%	73%	60%	48%

Note: This table computes the losses as a percent of total bank equity that the regulator could suffer. For more details, see Section 3.7.

The conditional expectation in (3.24) reflects the assumption that the regulator computes the probabilities over $\frac{p_t^h}{p_{t-1}^h}$ conditional on the same prior, p_t , that the banks are using to choose their lending standards. In other words, I do not assume that the regulator has different information about the state of the economy than private banks have. It would be easy to incorporate the case in which the regulator has different information. In that case the capital requirement would also change to encourage banks to behave according to the regulator's priors.

Table 3.3 compares how different capital requirements would affect regulator losses for VaR confidence levels of 98%, 95% and 90%.¹⁶ The first row of the table reports the regulator losses for each VaR confidence level for the benchmark calibration of a 4% capital requirement.

As the capital requirement rises, the size of potential regulator losses falls for each VaR confidence level. There are two channels through which the capital requirement

¹⁶To generate the table, banks' prior is set to 0.75, and regulator losses are computed at the level of house price growth such that an equivalent or worse loss occurs 2%, 5% or 10% of the time.

operates. First, it operates on a quantity dimension. Raising the capital requirement lowers the amount of leverage banks can use to finance a loan. In the event of a bad real estate price shock, this means that capital is thus able to absorb more of the losses. Second, the capital requirement operates on a price dimension. Because I assumed that for banks raising capital is a more expensive form of finance than borrowing ($R_t^E \geq R_t^B$), when higher capital requirements force banks to finance a larger set of their lending with equity then banks need to raise their lending standards to lend to borrowers who are more profitable. That is, when banks' costs increase, banks need to be more selective in terms of to which investors to lend.

Figure 3.8 plots the optimal capital requirement as a function of bank beliefs for target losses of 75% and 100% to ensure that the probability of observing a crisis is fixed at 2%.¹⁷

Figure 3.8 shows that capital requirements should lean against bank beliefs. In general, the VaR regulator should raise capital requirements when the banks are more optimistic and therefore more exposed to bad shocks. When the banks are more pessimistic and less exposed, they need lower capital requirements. However, rational banks usually have optimistic beliefs when it is less likely that a bad shock will happen. This force generates a non-monotone response of capital requirements.

Figure 3.8 also shows the effect of the regulator's loss tolerance. When the tolerance switches from 75% to 100% of bank capital, the regulator is allowing larger losses to happen within its 98% confidence interval. Because these 100% losses happen less frequently in general, the capital requirements needed to combat them are lower than those required to combat losses of 75%.

¹⁷When discussing Basel III, the Basel Committee claims that there is a 5% probability of a Basel Committee member country facing a crisis in any given year and discusses reducing this probability by 1%, 2% or 3% (Basel Committee on Banking Supervision 2010a).

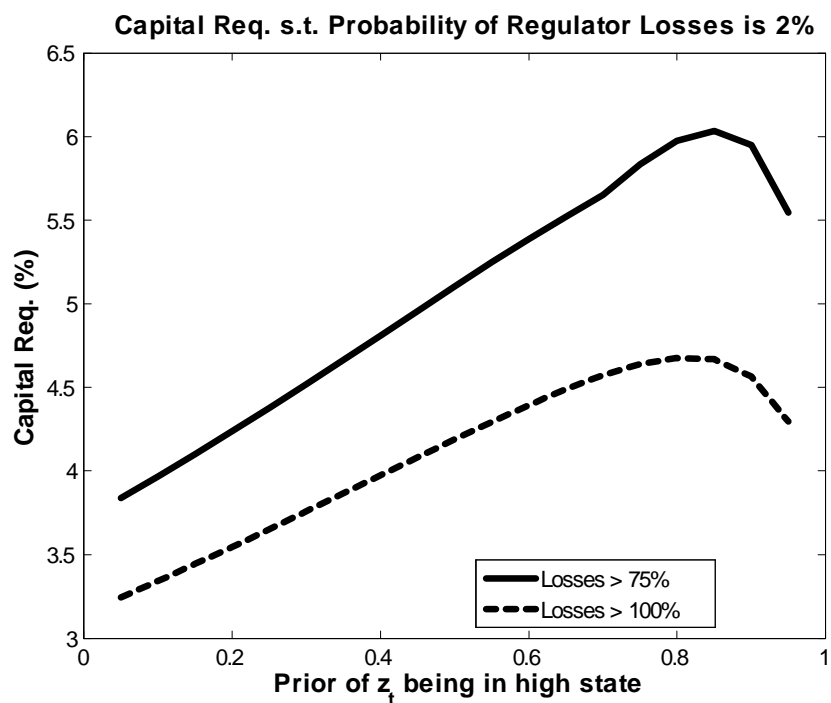


Figure 3.8: **Capital Requirements and Banks' Beliefs.** This figure plots, as a function of the prior about the persistent part of price growth, the capital requirement such that the probability of the regulator losing more than 75% or 100% of banking system capital is fixed at 2%.

To illustrate the link between house price growth and VaR policy based upon bank beliefs, I plot in Figure 3.9 the VaR capital requirement corresponding to the house price growth scenarios I presented in Section 3.6: a sequence of two periods of 2%, 5% and 8% growth respectively.

In each panel of Figure 3.9, the VaR capital requirement very closely follows the pattern of risk observed in the corresponding panels of Figures 3.6 and 3.7. In Panel A, the gradual increase in bank risk in response to 2% house price growth is met with a gradual increase in the capital requirement. In Panels B and C, the non-monotone response of risk means that the VaR capital requirement is non-monotone as well. As before, this non-monotonicity arises because optimistic banks lower their lending standards and become more exposed to bad shocks, but the risk of those bad shocks is smaller since rational bankers only become optimistic when it is less likely that a bad shock occurs. Figure 3.9 also shows that a house price growth rate of 5% (Panel B) requires a higher VaR capital requirement than a house price growth rate of 8% (Panel C). This occurs because risk is higher in the case of a 5% house price growth rate.

3.8 CONCLUSIONS

This chapter proposed a quantitative model of lending standards with two frictions generating inefficient credit: 1) lenders' moral hazard from limited liability (that can also be interpreted as deposit insurance or government guarantees), and 2) imperfect information about the persistence of real estate price growth, which generates the possibility of rational mistakes. I studied which patterns of real estate price growth and banks' beliefs could serve as early warning indicators of a crisis. With rational agents, even if lending standards are monotonically decreasing in optimism, the more

House Price Dynamics and VaR Capital Req.

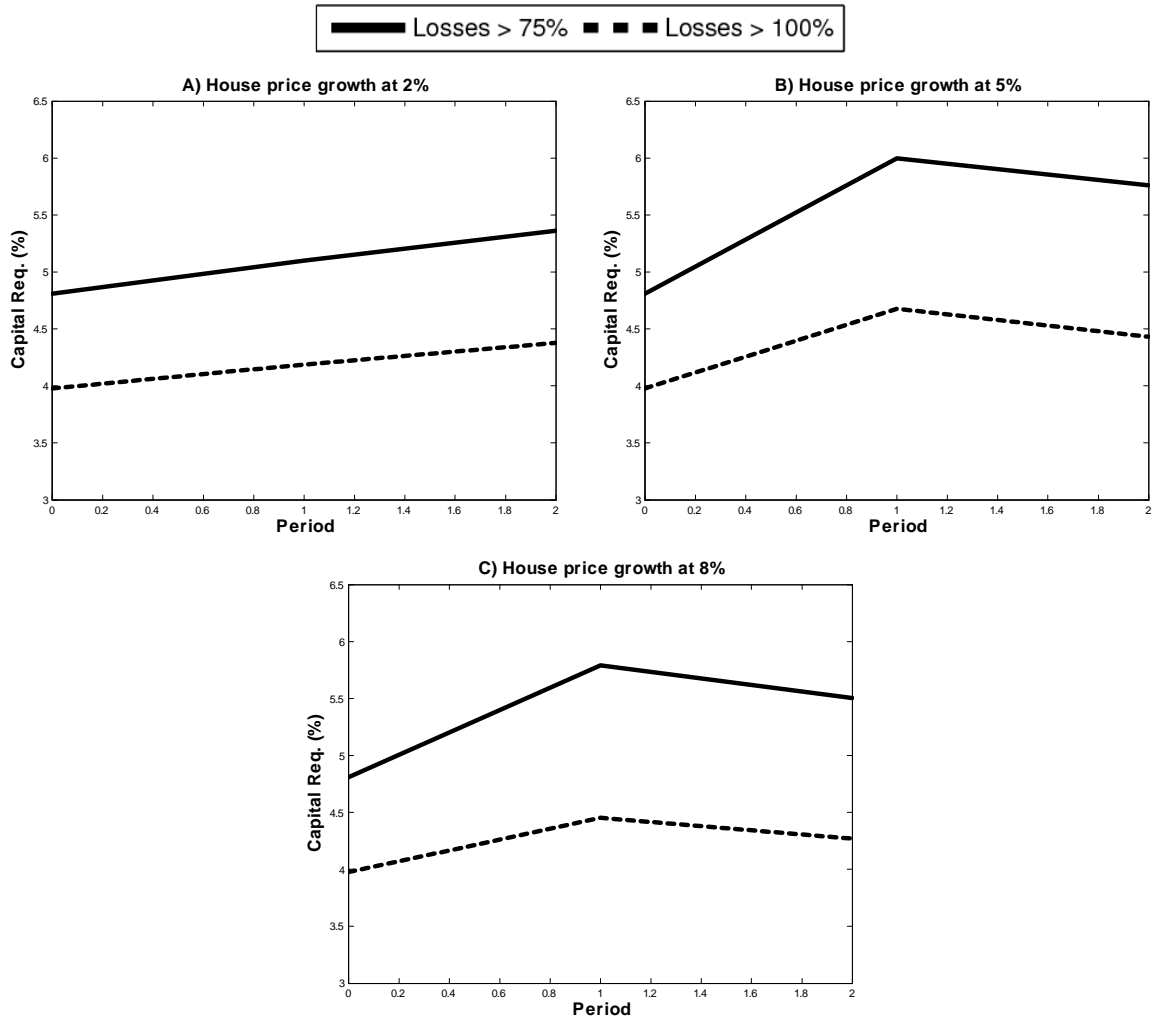


Figure 3.9: **House Price Dynamics and Value-at-Risk Capital Requirements.** This figure plots the Value-at-Risk capital requirement such that the probability of the regulator losing more than 75% or 100% of banking system capital is fixed at 2% for different house price growth rates.

dangerous booms are not monotonically increasing in optimism. When the banks are more optimistic they are more exposed to bad shocks. However rational banks usually have optimistic beliefs when it is less likely that a bad shock happens.

Finally, I proposed a Value at Risk (VaR) rule to implement countercyclical capital requirements. Capital requirements can incentivize banks to pick the socially optimal level of lending standards. Capital requirements should be state-contingent and lean against lenders' beliefs by tightening in periods of price optimism. However, they should be not monotone, as risk is not monotone in beliefs.

Future extensions of this chapter may include bringing the model into a general equilibrium setting, analyzing the welfare implications of the VaR rule, and studying cases in which banks' beliefs could be irrational and diverge from those of a rational regulator.

CHAPTER 4

LENDER EXPECTATIONS AND MORTGAGE MARKET DYNAMICS: A PANEL DATA STUDY

4.1 INTRODUCTION

One often-cited cause of the recent U.S. financial crisis is that mortgage lending standards in the pre-crisis years were too lax.¹ Most of the literature so far has focused on the role securitization played in lowering lending standards. For example, Keys et al. (2010) find that loans just above a credit score cutoff, making them easier to securitize, default 20% more often than loans with similar risk characteristics just below the cutoff. There is also a new literature that studies the role played by optimistic lender expectations.² Foote et al. (2012), for example, argue that overly optimistic beliefs about house prices were a main feature of pre-crisis lending decisions. Understanding both of these channels is important in order to prevent future crises.

This chapter contributes along the expectations dimension by testing the role of lender expectations about housing prices and borrower incomes on the dynamics of housing markets. I employ a Metropolitan Statistical Area (MSA) level data set that includes individual mortgage loan application data from the Home Mortgage Disclosure Act (HMDA) and bank branching data from the FDIC Summary of Deposits

¹See, for example, Dell’Ariccia et al. (2012), Demyanyk and Van Hemert (2011), Favilukis et al. (2012), Keys et al. (2010 and 2012), or Maddaloni and Peydro (2011).

²See, for example, Brueckner et al. (2012), Cheng et al. (2013), Foote et al. (2012) and Goetzmann et al. (2012).

Survey to test whether a proxy for lender expectations is related to changes in lenders' mortgage denial rates in the 2005-2011 period. Moreover, a key component of this study is to test whether overly optimistic lender expectations can be observed in the data and whether this optimism coincided with overzealous mortgage lending.

As lender expectations are difficult to measure directly, I employ a new proxy to capture them. The proxy I study is the change in the number of lender branch locations. Because new branch locations are costly to open and operate, only lenders that expect favorable future lending conditions in an area will choose to open them. Similarly, lenders expecting a deterioration in future lending conditions in an area will choose to close branches. Hence, banks' branching decisions are likely a good indicator of banks' expectations.

First, I use my data set to study whether bank branching decisions are a reliable proxy for banks' expectations. Specifically, I examine whether banks opening new branches in an MSA exhibit lower mortgage denial rates on properties located within that same MSA. A novel feature of my data set is that I am able to exploit the heterogeneity in lenders' expectations within the same MSA by comparing the lending behavior of banks that opened new branches to those that did not.

Second, I estimate separately the response functions of individual lenders' branching and mortgage denial rate decisions to the same sequence of changes in MSA conditions. By comparing these separate response functions, I am able to study whether banks that are overly optimistic in terms of opening more branches than average also engage in overzealous mortgage lending.

My results show that lenders that invest in new branches in a particular MSA significantly lower their denial rates on mortgage loans for properties within that same MSA. When I break my sample by banks' asset sizes, I find that this relationship is more pronounced for mid-size banks with assets between \$2 billion and \$10 billion.

These results suggest that bank branching decisions may be a reliable proxy for bank expectations.

When I examine lenders' MSA-level branching and mortgage denial decisions separately, I find lenders that respond to positive movements in house prices and borrower incomes by opening (closing) more branches than average also lower (raise) their mortgage denial rates by more than average. This result suggests that banks that are more optimistic on average lower their lending standards by more than average.

To explore the robustness of my results, I redo my analysis by lien priority, focusing on the pre-crisis period. Loans secured by first liens are inherently less risky, as the lender is first in line to capture the underlying value of the mortgage property should the loan default. Second liens and loans not secured by a lien, on the other hand, carry more risk. One would expect that lender expectations would play a large role in the approval/denial decision of second liens and unsecured loans. However, I find that my expectations proxy does a better job explaining the behavior of lenders' first lien approval/denial decisions.

There is an existing literature that addresses the relationship between expectations about housing prices and lending standards. Gete and Tiernan (2014) finds using a quantitative model that under imperfect information about the persistence of house price growth, lenders who observe a sequence of positive house price shocks will rationally expect future price growth and lower their lending standards in response. Brueckner et al. (2012) and Goetzmann et al. (2012) provide empirical evidence that lenders extrapolated pre-crisis housing price trends to make subprime lending decisions. Mian and Sufi (2009), however, finds that increased mortgage credit in areas with high levels of subprime lending was driven largely by credit supply factors rather than by housing price expectations.

My study is also related to Cheng et al. (2013), Cortes (2012), and Dell’Arricia et al. (2008). Cheng et al. (2013) provides evidence that overly optimistic lender expectations may have negatively influenced lending standards. The paper compares the performance of the personal home transactions of mid-level managers in securitized finance with those of uninformed control groups and finds that the transactions of securitization agents performed worse. The authors conclude that this result signals distorted beliefs of agents in the mortgage market during the pre-crisis period. My study, in contrast, employs branching decisions as a new proxy to determine whether optimistic beliefs were present in the housing market. Cortes (2012) examines the behavior of local lenders, i.e. lenders who operate branches in the same county in which they engage in mortgage lending, in the presence of home price shocks and finds that local lenders have better information about home-price fundamentals than non-local lenders. The author finds that in general, the share of local lending in a market fell as home prices grew rapidly. I only consider local lending in my analysis, but still find evidence of overly optimistic behavior by local lenders due to changes in prices and borrower incomes. Dell’Arricia et al. (2008) studies the determinants of denial rates at the MSA level and find that denial rates from 2001-2006 fell as home prices, population and average income rose. They find that credit boom conditions and market structure also mattered. My analysis addresses some of the same denial rate determinants, but approaches the question at the bank-MSA level.

The remainder of the chapter is organized as follows. Section 4.2 discusses the conceptual framework of the exercise. Section 4.3 presents the data. Section 4.4 describes the empirical methodology. Section 4.5 discusses the empirical results. Section 4.6 offers a robustness check. Section 4.7 concludes.

4.2 CONCEPTUAL FRAMEWORK

Consider a stylized model of banks and borrowers similar to that presented in Chapter 3. Banks and borrowers randomly meet to form 1-period mortgage lending arrangements, and banks must decide whether or not to lend to the borrowers they meet.³ Banks' lending decisions hinge on their borrower's income. Borrowers' income is made up of two components, an idiosyncratic component and an aggregate component. The idiosyncratic component is distributed as in Figure 4.1, and the aggregate component is composed of two unobservable parts: 1) a persistent component and 2) a transitory noise component. Banks are able to observe their borrower's idiosyncratic component of income but must form an expectation about the level of the aggregate component, which is observed at the end of the period after lending decisions are made. Banks form this expectation based upon past observations of the aggregate component of income using Bayesian updating. Ideally, the bank would only consider the persistent component of aggregate income in its forecast, but it is possible that a positive transitory noise shock could be interpreted as a positive change in the persistent component. Hence, episodes of rational optimism are possible.

A bank uses information regarding its borrower's idiosyncratic income, its own borrowing costs, and its expectation about the aggregate component of income to set lending standards. That is, given the bank's information set, it will set an approval cutoff such that borrowers with idiosyncratic income above that cutoff will receive a loan and borrowers below the cutoff will not. Figure 4.1 depicts the approval cutoff. A bank that expects the aggregate component of income to be high will rationally lower its lending standards and lend to borrowers with lower incomes than it would have before. However, if the bank's expectation was formed after observing a positive

³For simplicity, I abstract from borrowers' demand decisions.

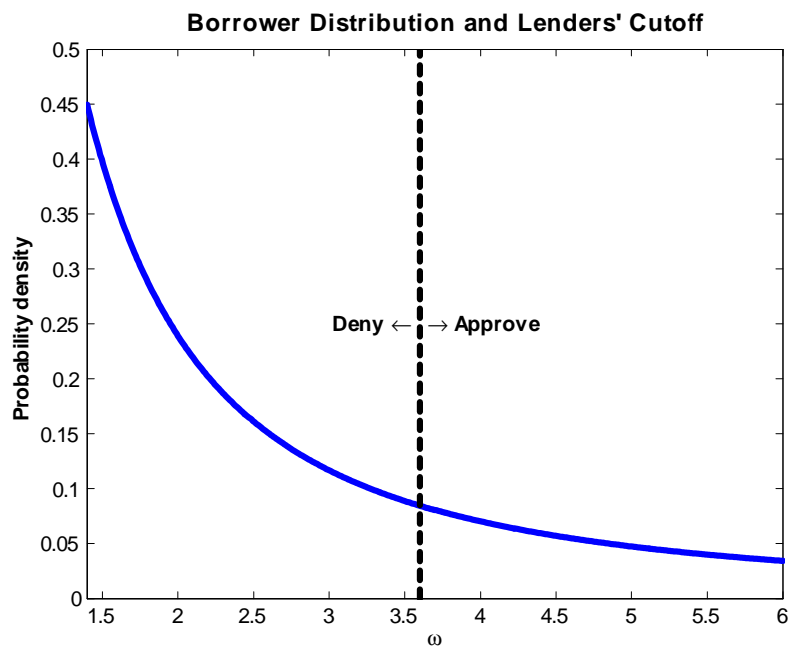


Figure 4.1: **Distribution of Borrowers and Lending Standards.** This picture plots the Pareto distribution of borrowers' idiosyncratic characteristics (ω) and banks' lending standards. Borrowers to the right of the approval cutoff receive loans, borrowers to the left do not. The approval cutoff, or lending standard, changes with the bank's expectation about real estate price growth.

shock to the transitory noise component, then lower lending standards may imply end-of-period losses for the bank. This would represent an instance of a rational but optimism-driven relaxation in lending standards.

Taking this model to the data, since I cannot observe banks' expectations directly, I infer them from bank behavior. Specifically, I employ bank branching decisions as a proxy for bank expectations. Banks that are enthusiastic about lending opportunities in a particular area will open a new branch to draw in and meet with more potential customers. If this behavior also translates into lower lending standards in the form of lower mortgage denial rates, then I provide evidence of an optimism-driven relaxation in lending standards.

4.3 DATA

My principal data sets are publicly available and include U.S. home mortgage application data from the Home Mortgage Disclosure Act and bank branch data from the FDIC Summary of Deposits Survey. My control variables include banking variables from the "Consolidated Reports of Condition and Income" (Call Reports) collected by U.S. bank regulatory authorities, MSA-level demographic and economic data from the Bureau of Economic Analysis and MSA-level home price data from Freddie Mac.

4.3.1 HOME MORTGAGE DISCLOSURE ACT (HMDA) DATA

The Home Mortgage Disclosure Act was enacted in 1975, and requires mortgage lending institutions to report data on mortgage loan applications to gauge compliance with fair lending laws and to guide public investment in housing. The data

coverage includes mortgage applications received by depository institutions and mortgage finance companies with branch offices in MSAs. The data do not cover mortgage applications received by small or primarily rural depository institutions.

HMDA data include characteristics about mortgage loan itself, information regarding whether the loan was approved or denied, borrower demographic and income characteristics, as well as information regarding the underlying property and its location. My sample starts in 2005 and runs through 2011. HMDA data cover approximately 95% of the total volume of home mortgage originations in the U.S. in this period.⁴ Because my proxy for lender expectations is only available for banks and savings institutions, I restrict my analysis to the application data reported by these institutions. With this restriction, my data account for approximately 40% of the lending activity captured by HMDA. The remaining fraction of lending activity was reported by mortgage finance companies.

My primary interest in the HMDA data is computing denial rates by lender in a particular MSA in a particular year. To ensure that my comparison of denial rates across lenders is sensible, I restrict my analysis to applications for conventional home purchase loans where the underlying property is a one-to-four family home that will be owner-occupied. Furthermore, I examine only those applications with clear approval or denial decisions. That is, I include applications where the lender either originated the loan, denied the loan, or the loan was approved but not accepted.⁵ After all restrictions, my data set includes approximately 12% of the lending activity captured by HMDA. I define the denial rate as the total number of applications denied by a lender in a particular MSA in a particular year divided by the total number of

⁴Dell’Ariccia et al. (2008) provide estimates of HMDA coverage rates by year.

⁵I exclude applications that were withdrawn by the applicant, application files that were closed due to incompleteness, loans that were purchased by the lender, or any preapproval requests.

applications received by a lender in a particular MSA in a particular year.

$$denial_rate_{ikt} = \frac{apps_denied_{ikt}}{apps_received_{ikt}} \quad (4.1)$$

where i represents the lender, k represents the MSA and t represents the year. I compute the change in the denial rate as the difference in the denial rate between years t and $t - 1$:

$$\Delta denial_rate_{ikt} = denial_rate_{ikt} - denial_rate_{ik,t-1} \quad (4.2)$$

In order to use the HMDA data alongside data from the Summary of Deposits Survey and Call Reports, I must link records in the HMDA data to each financial institution's unique RSSD number. To do this, the HMDA data include a unique identifier for each lender based upon the combination of the lender's agency code and HMDA respondent identification number.⁶ Those institutions listed as filing with the Office of the Comptroller of the Currency report their charter number as their respondent identification number, those filing with the Federal Reserve System report their RSSD number, those filing with the FDIC report their certificate number and those filing with the Office of Thrift Supervision report their docket number. I match these numbers to the related fields in the Call Report in order to find each institution's RSSD number.

4.3.2 SUMMARY OF DEPOSITS SURVEY DATA

The Summary of Deposits Survey contains data on the location and deposits of branch offices for all FDIC-insured institutions as of June 30th of each year. To use bank branching decisions as a proxy for expectations, I first compute the total number of branch offices in an MSA for each lender in a given year. I then compute

⁶The agency code represents the regulatory agency with which the lender files.

the percent change in the total number of branch offices for each lender in a given year, accounting for any mergers and acquisitions.

$$\% \Delta branches_{ikt} = \frac{branches_{ikt} - branches_{ik,t-1}}{branches_{ik,t-1}} \quad (4.3)$$

where i represents the lender, k represents the MSA and t represents the year.

4.3.3 SUMMARY STATISTICS

In what follows, I define a bank or a lender as the regulatory top holder financial institution. That is, where possible I aggregate observations up to the bank holding company level. In addition, because I study year-on-year changes in some of my variables of interest, I also make adjustments for merger and acquisition activity using data available from the Federal Reserve Bank of Chicago.⁷ Table 4.1 contains summary information about variable definitions and data sources.

Table 4.2 reports summary statistics. In Table 4.2, the mean year-on-year change in the denial rate within my sample is around 0.02, reflecting that on average denial rates increased by 2%. The maximum and minimum values for the change in the denial rate reflect a year-on-year change from a 0% denial rate to a 100% denial rate and vice versa. In each of these cases, the bank received less than five loan applications per year and either denied or approved all of them. The mean percentage change in bank branches, after adjusting for mergers and acquisitions, is close to 15% in my sample. House prices fell on average across all MSAs by 2.34% from 2005-2011. The most rapid decline in house prices occurred in the Las Vegas, Nevada MSA during 2008 and the most rapid increase occurred in the Midland, Texas MSA during 2006. Per capita income rose on average across all MSAs by 2.85% from 2005-2011. The most

⁷Because merger and acquisition activities and the associated changes in bank branch locations may occur for reasons other than lender expectations about mortgage lending prospects, I exclude these observations from my analysis.

Table 4.1: Variables and Sources

Variable Name	Definition	Source
Data at the Bank-Year-MSA Level		
$\Delta denial_rate_{ikt}$	Annual difference in the ratio of denied applications to total applications in an MSA for a particular bank	HMDA
$\% \Delta branches_{ikt}$	Annual percentage change in the number of bank branches within an MSA for a particular bank	FDIC Summary of Deposits Survey
Data at the Bank-Year Level		
Bank assets	Total bank assets	Call Report
Data at the MSA-Year Level		
$\% \Delta prices_{kt}$	Annual percentage change in housing prices in the MSA	Freddie Mac
$\% \Delta income_{kt}$	Annual percentage change in per capita income in the MSA	BEA
$\% \Delta population_{kt}$	Annual percentage change in population in the MSA	BEA

rapid increase and decrease in income occurred in the New Orleans, Louisiana MSA in 2006 and in the Midland, Texas MSA in 2009, respectively. Lastly, population across all MSAs rose by close to 1% from 2005-2011. The most rapid decline in population occurred in New Orleans, Louisiana in 2006 following Hurricane Katrina. The most rapid increase in population occurred in Palm Coast, Florida during 2006.

4.4 EMPIRICAL METHODOLOGY

I first test the relationship between bank branching and denial rate decisions using a simple regression. My hypothesis is that lenders that increase the size of their branch network in a given MSA in a particular year will also lower their mortgage denial rate in that MSA in that year. That is, lenders that invest in opening branches do so because they expect more favorable lending conditions, which will then also be reflected in lower mortgage denial rates. My simple regression takes the following

Table 4.2: Summary Statistics

Variable Name	Obs.	Mean	Std. Dev.	Min	Max
Data at the Bank-Year-MSA Level					
$\Delta denial_rate_{ikt}$	4,163	0.0193	0.1635	-1.0000	1.0000
$\% \Delta branches_{ikt}$	4,163	14.80%	45.97%	-93.33%	966.67%
Data at the Bank-Year Level					
Bank assets (in 000's)	2,075	9,986,037	97,931,759	28,657	2,187,631,000
Data at the MSA-Year Level					
$\% \Delta prices_{kt}$	1,232	-2.34%	6.14%	-36.11%	25.65%
$\% \Delta income_{kt}$	1,232	2.85%	4.45%	-22.42%	33.11%
$\% \Delta population_{kt}$	1,232	1.02%	1.36%	-25.41%	9.52%

form:

$$\Delta denial_rate_{ikt} = \beta_1 + \beta_2 \% \Delta branches_{ikt} + \varepsilon_{ikt} \quad (4.4)$$

where $\Delta denial_rate_{ikt}$ represents the difference in the denial rate between years t and $t - 1$ for bank i in MSA k and $\% \Delta branches_{ikt}$ represents the percent change in the number of branches between years t and $t - 1$ for bank i in MSA k . I run this regression for the full sample of banks as well as for different samples of banks categorized by size.

To further analyze the relationships I observe from this simple regression, I explore the effect of different MSA-level factors on the banks' decisions about branching and mortgage application denials separately.⁸ First, I examine the impact of changes in population, changes in per capita income, and changes in house prices on a bank's decision to open or close its branch locations in a given MSA.⁹ In order to capture individual banks' reactions to these different MSA conditions, I also include an

⁸I conduct analyses of the branching and denial decisions separately to avoid issues with multicollinearity.

⁹Hannan and Hanweck (2008) find that population and per capita income explain the number of bank branches present in a given MSA.

interaction term in my specification. The coefficient on this term will measure the sensitivity of individual banks to changes in either home prices or per capita income in terms of branching decisions. My specification takes the following form:

$$\% \Delta branches_{ikt} = \left(\begin{array}{l} \alpha_i D_i + \beta_1 \% \Delta population_{k,t-1} + \\ + \beta_2 \% \Delta income_{k,t-1} + \\ + \beta_3 \% \Delta prices_{k,t-2} + \\ + \gamma_i (D_i * selected_control) + \varepsilon_{ikt} \end{array} \right) \quad (4.5)$$

where D_i is a dummy variable for bank i , $\% \Delta population_{k,t-1}$ is the lagged percent change in population in MSA k , $\% \Delta income_{k,t-1}$ is the lagged percent change in per capita income in MSA k , $\% \Delta prices_{k,t-2}$ is the lagged percent change in house prices in MSA k , and $selected_control$ can be either $\% \Delta prices_{k,t-2}$ or $\% \Delta income_{k,t-1}$. I focus on lagged MSA controls because changes in branches are measured July 1 to June 30, while my controls are measured January 1 to December 31.

Second, I examine the impact of the same MSA controls on changes in banks' mortgage denial rates.¹⁰ I again include an interaction term with two separate specifications:

$$\Delta denial_rate_{ikt} = \left(\begin{array}{l} \lambda_i D_i + \psi_1 \% \Delta population_{k,t-1} + \\ + \psi_2 \% \Delta income_{k,t-1} + \\ + \psi_3 \% \Delta prices_{k,t-2} + \\ + \theta_i (D_i * selected_control) + \varepsilon_{ikt} \end{array} \right) \quad (4.6)$$

where the independent variables have the same meaning as in equation (4.5) and $selected_control$ can be either $\% \Delta prices_{k,t-2}$ or $\% \Delta income_{k,t-1}$. Again, the coefficient on the interaction term will measure the sensitivity of individual banks to

¹⁰Dell'Araccia et al. (2008) find that population, average income and house price appreciation can explain mortgage denial rates in an MSA.

changes in either home prices or per capita income in terms of changes in mortgage denial rates.

Because my interest is in measuring and examining the effects of expectations, I study whether banks that are more sensitive to changes in either home prices or per capita income are opening (closing) branches while at the same time lowering (raising) their denial rate. This relationship would show up in a comparison of γ_i , my measure for the sensitivity of bank i 's branching decisions to changes in MSA conditions, with θ_i , my measure for the sensitivity of bank i 's denial rate modifications in response to changes in MSA conditions.

4.5 RESULTS

The first specification of equation (4.4) that I test includes all of the banks in my sample, and I find that the relationship between branching decisions and the mortgage denial rate is negative and significant, confirming my hypothesis that branching decisions may be a reliable proxy for bank expectations. When I restrict my sample to banks of certain sizes, I find varying degrees of significance. Table 4.3 reports these results.

Banks with assets between \$2 billion and \$10 billion, which account for approximately 13% of the number of banks in my sample, tend to lower mortgage denial rates in MSAs where they are increasing the number of branch locations. However, smaller banks and very large banks do not exhibit a significant relationship between branch openings and changes in mortgage denial rates.

To explore whether I can find evidence of lender optimism in the data, I run the regressions in equations (4.5) and (4.6) for my whole sample of banks and the subsample of banks with assets between \$2 billion and \$10 billion. I want to compare

Table 4.3: Simple Regression Results, Full Sample

Dep. var.: $\Delta denial_rate_{ikt}$	All banks	Assets <\$0.9B	Assets \$0.9B-\$2B	Assets \$2B-\$10B	Assets >\$10B
$\% \Delta branches_{ikt}$	-0.012** (0.006)	-0.014 (0.010)	0.025 (0.017)	-0.055*** (0.019)	-0.007 (0.007)
Constant	0.021*** (0.003)	0.018*** (0.005)	0.013* (0.008)	0.030*** (0.008)	0.023*** (0.003)
Observations	4163	1713	438	550	1462
No. of Banks	962	617	162	129	54

Notes: Standard errors are in parentheses. * denotes significance at 10%, ** at 5%, and *** at 1%. The change in the denial rate is computed from HMDA and the percent change in bank branches is computed from the Summary of Deposits Survey. Results reported for years 2005-2011.

γ_i , my measure for the sensitivity of bank i 's branching decisions to changes in MSA conditions, with θ_i , my measure for the sensitivity of bank i 's denial rate modifications in response to changes in MSA conditions.

In Figure 4.2, I produce a scatter plot of γ_i and θ_i for my full sample of banks. Support for the expectations channel is present if in Figure 4.2 we observe a negative relationship between the two coefficients. I interpret such a result as evidence that banks responding to higher house prices or per capita income by opening (closing) more branches are also responding by lowering (raising) their denial rates to a larger degree. Figure 4.2 indeed illustrates that the expectations channel with regards to changes in both house prices and per capita income appears to drive the negative relationship between changes in bank branches and changes in bank denial rates.

Figure 4.3 plots the coefficients γ_i and θ_i for the subsample of banks with assets between \$2 billion and \$10 billion. Again we see a negative correlation between banks' sensitivity to changes in house prices and per capita income.

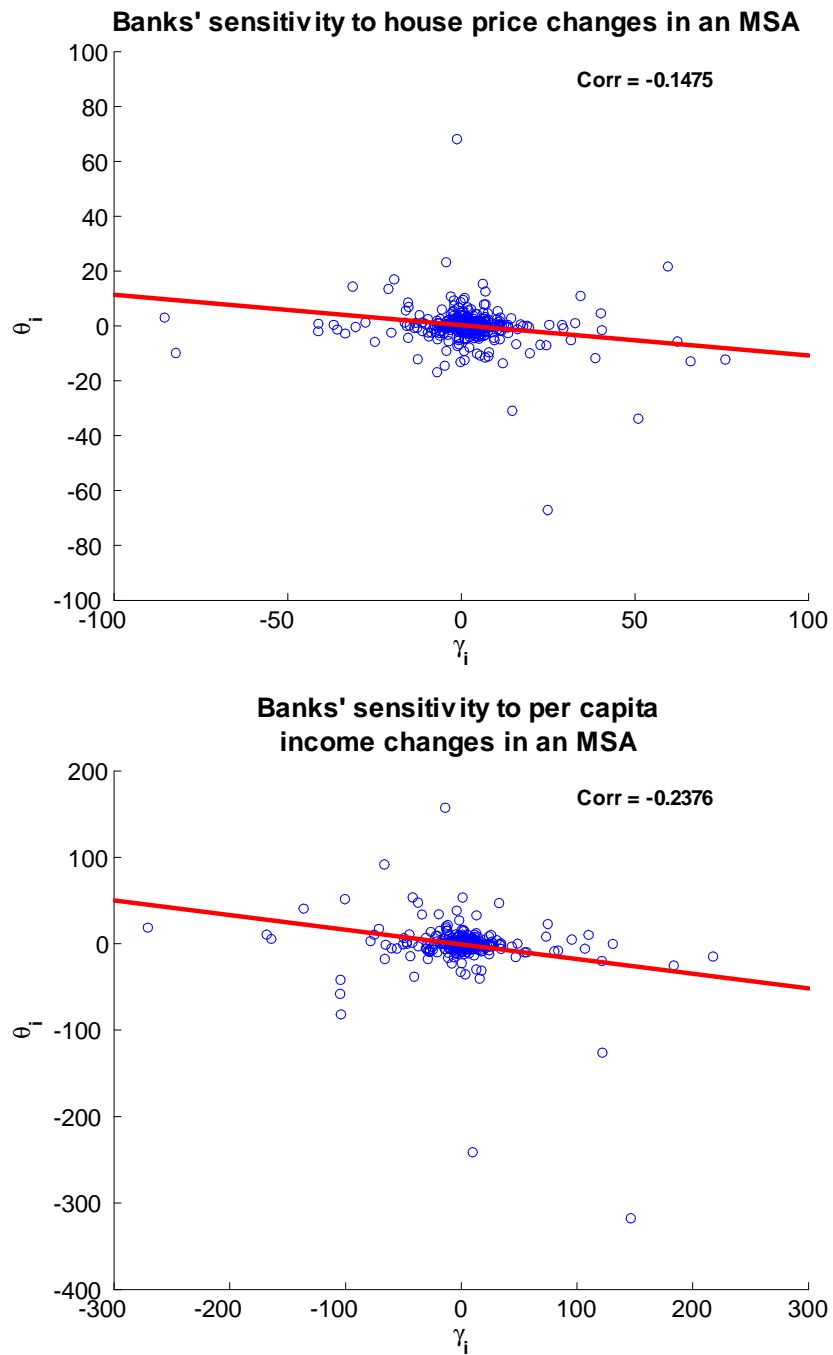


Figure 4.2: **Banks' sensitivity to house price and per capita income changes, whole sample.** Sensitivity of individual banks' branch openings (γ_i) and denial rates (θ_i) in response to changes in MSA conditions from 2005-2011. Data are shown for all banks.

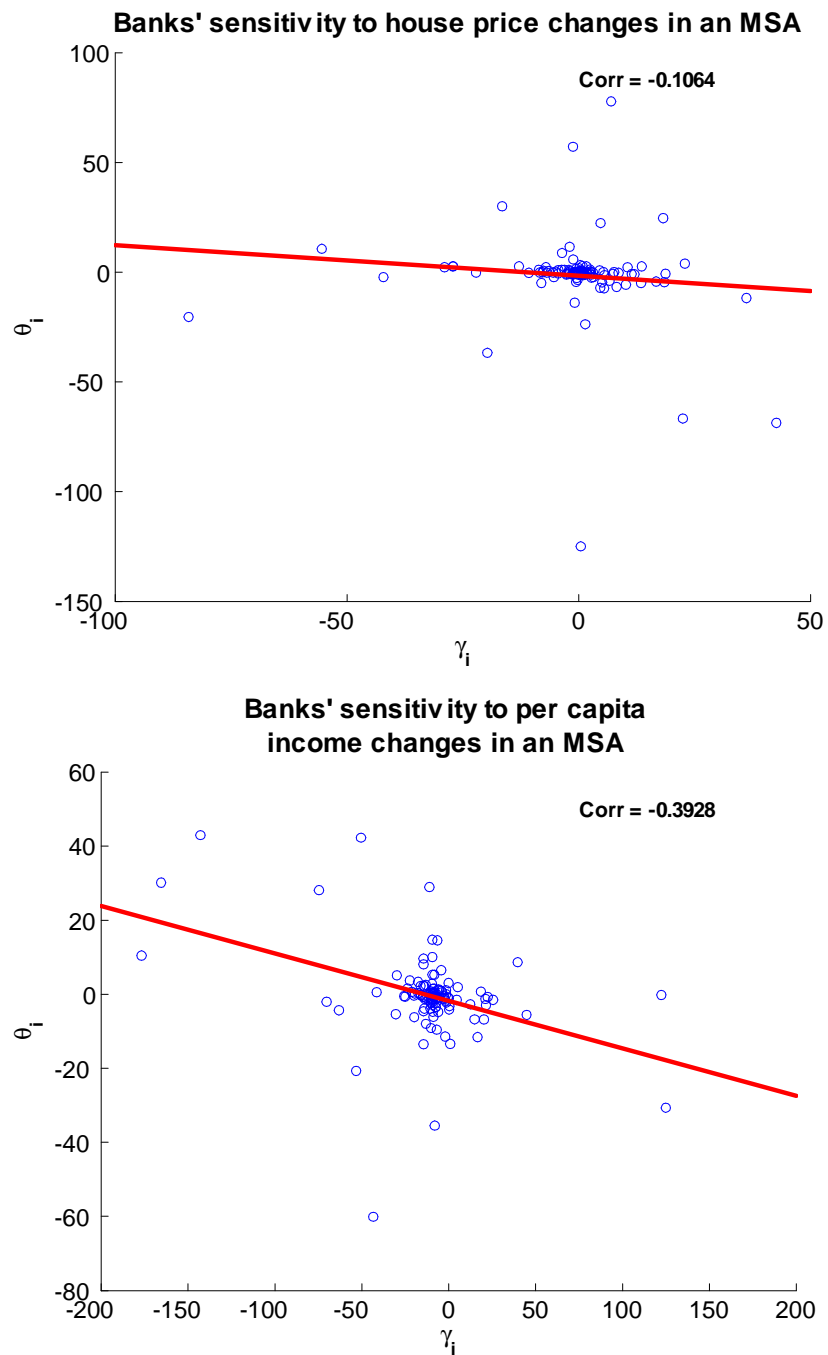


Figure 4.3: **Banks' sensitivity to house price and per capita income changes, \$2 billion to \$10 billion in assets.** Sensitivity of individual banks' branch openings (γ_i) and denial rates (θ_i) in response to changes in MSA conditions from 2005-2011. Data are shown for banks with assets between \$2 billion and \$10 billion.

Table 4.4: Simple Regression Results, First Liens Only

Dep. var.: $\Delta denial_rate_{ikt}$	All banks	Assets <\$0.9B	Assets \$0.9B-\$2B	Assets \$2B-\$10B	Assets >\$10B
$\% \Delta branches_{ikt}$	-0.007 (0.008)	-0.038* (0.021)	0.018 (0.024)	-0.036** (0.018)	0.006 (0.010)
Constant	0.016*** (0.004)	0.028** (0.013)	0.012 (0.013)	0.012 (0.008)	0.017*** (0.006)
Observations	1737	387	251	351	748
No. of Banks	633	314	156	127	52

Notes: Standard errors are in parentheses. * denotes significance at 10%, ** at 5%, and *** at 1%. The change in the denial rate is computed from HMDA and the percent change in bank branches is computed from the Summary of Deposits Survey. Results reported for first liens only during pre-crisis years 2005-2007.

4.6 ROBUSTNESS

As a robustness check, I repeat my analysis by lien status for the pre-crisis period 2005-2007. Because mortgages based on subordinated and unsecured liens are inherently more risky, it is likely that the expectations channel would be even more apparent on these types of loans in the lead-up to the crisis. In the HMDA data, lien status is reported for loan applications and originations as either a first lien, a subordinate lien, or not secured by a lien. Tables 4.4 and 4.5 report the results of the simple regression for first lien and subordinate/unsecured liens respectively. The results in Table 4.4 are fairly similar to those in Table 4.3 and show that the change in denial rates of banks with assets less than \$900 million and banks with assets between \$2 billion and \$10 billion is negatively related to branch openings. All results in Table 4.5 are insignificant, suggesting that branching decisions may not be a reliable proxy for expectations about subordinate and unsecured lien lending prospects.

Table 4.5: Simple Regression Results, Subordinate and Unsecured Liens Only

Dep. var.: $\Delta denial_rate_{ikt}$	All banks	Assets	Assets	Assets	Assets
		<\$0.9B	\$0.9B-\$2B	\$2B-\$10B	>\$10B
$\% \Delta branches_{ikt}$	0.008 (0.009)	-0.014 (0.044)	0.037 (0.028)	-0.017 (0.038)	0.008 (0.010)
Constant	0.004 (0.005)	0.017 (0.017)	-0.011 (0.016)	0.007 (0.013)	0.004 (0.006)
Observations	1313	182	164	248	719
No. of Banks	413	157	111	107	47

Notes: Standard errors are in parentheses. * denotes significance at 10%, ** at 5%, and *** at 1%. The change in the denial rate is computed from HMDA and the percent change in bank branches is computed from the Summary of Deposits Survey. Results reported for subordinate and unsecured liens during pre-crisis years 2005-2007.

Figure 4.4 plots the coefficients of the interaction terms in the regressions of equations (4.5) and (4.6) for the first lien sample. This plot resembles those of Figures 4.2 and 4.3.

4.7 CONCLUSION

I examine at the MSA level bank branching decisions as a proxy for lender expectations and test whether this proxy can explain changes in lenders' mortgage denial rates. I find a significant negative relationship between banks' branch openings and their mortgage denial rates and find that this relationship is more pronounced for banks with assets between \$2 billion and \$10 billion. When I break the sample by lien status, I find similar results relationship for first lien mortgage applications, but find no such relationship for second lien and unsecured applications. These results provide support for the use of bank branching decisions as a proxy for lender expectations.

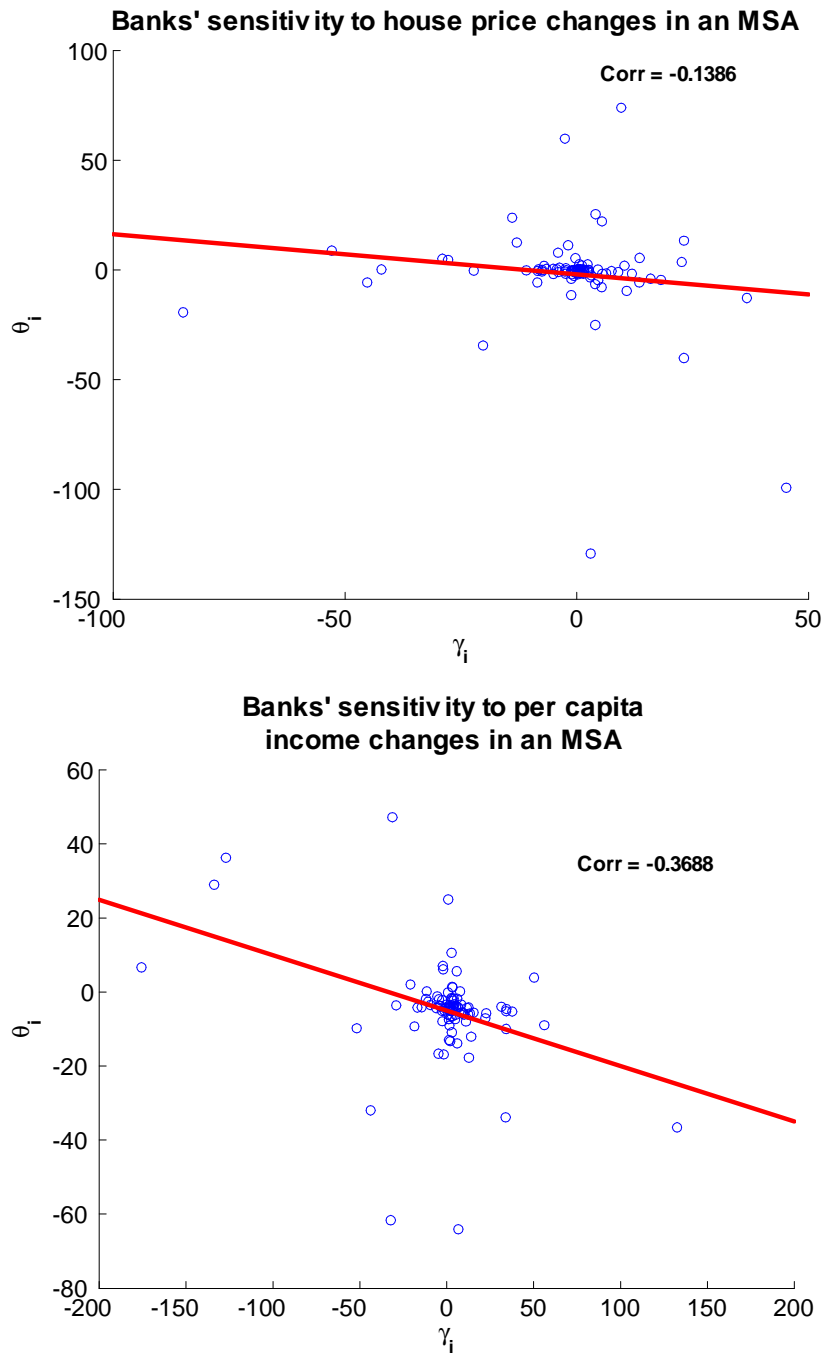


Figure 4.4: **Banks' sensitivity to house price and per capita income changes on first lien loan decisions, \$2 billion to \$10 billion in assets.** Sensitivity of individual banks' branch openings (γ_i) and denial rates (θ_i) on first lien loan applications in response to changes in MSA conditions in pre-crisis years 2005-2007. Data are shown for banks with assets between \$2 billion and \$10 billion.

Next, I compute the sensitivity of individual lenders' denial rate and branch opening decisions to changes in MSA level home prices and per capita income. Comparing the sensitivity of changes in the denial rate with changes in branch openings, I find evidence of an optimism-driven relaxation in lending standards. Optimistic lenders opening more branches than average in response to positive changes in home prices and borrower incomes also lower their mortgage denial rates by more than average. This evidence lends support to the effect of an expectations channel on lending standards.

APPENDIX A

APPENDIX FOR CHAPTER 2

A.1 DATA SOURCES

Data Sources for the Quantitative Model (Tables 2.1, 2.2, and 2.4 and Figure 2.2): Annual data from St. Louis FRED database for years 1987-2010. Series: Real GDP (GDPCA), Industrial Production Index (INDPRO), Total Loans and Leases (LOANS), Commercial and Industrial Loans (BUSLOANS), Total Equity to Total Assets (EQTA), GDP Deflator (GDPDEF), Return on Equity for all U.S. Banks (USROE), Delinquency Rate on All Loans (DRALACBS), Charge-Off Rate on All Loans (CORALACBS), Delinquency Rate on Business Loans (DRBLACBS), Charge-Off Rate on Business Loans (CORBLACBS), 6-Month London Interbank Offered Rate based on U.S. Dollar (USD6MTD156N).

Data Sources for the Panel Data Analysis (Tables 2.8-2.10): Data coverage includes years 2005-2011. Denial rates on U.S. home mortgage applications come from Home Mortgage Disclosure Act data provided annually by the FFIEC. Branch HHI data come from the FDIC Summary of Deposits Survey, which is reported annually as of June 30th. Annual MSA-level demographic and economic data, including population and per capita personal income, come from the Bureau of Economic Analysis's Personal Income Summary (CA1-3). MSA-level home price data come from the Freddie Mac House Price Index. The Saiz (2010) house supply elasticity measure comes directly from Table VI of that paper.

A.2 MODEL COMPUTATION PROCEDURES

A.2.1 SOLUTION ALGORITHM

Every period is a two-stage model, and I solve backwards for the optimal π_1 and π_2 . That is, in the second stage, I take the first stage aggregate lending intensity, Π_1 , as given and optimize π_2 . Then, in the first stage, banks solve for the optimal π_1 taking into account that the optimal π_2 is a function of π_1 . As discussed in Section 2.3.6 I compute two cases depending if banks internalize or not that π affects Π . The solution algorithm is as follows:

1. Discretize the range of π . I use 10,000 equally-spaced nodes between 0 and 1.
2. Generate a sequence of productivity shocks. Given an observation for z_{-1} and the process for productivity (equation 2.2), compute expectations about future productivity, z_1 and z_2 . Likewise, given an observation for z_1 , compute the one period ahead expectation for z_2 .
3. Compute the first and second stage informed and uninformed lending cutoffs ($\bar{\omega}_1$, $\bar{\omega}_2$, $A_1(\cdot)$, $A_1^U(\cdot)$, $A_2(\cdot)$) and the cutoff type ω for the first stage profitability indicator function, $\Omega_1(\cdot)$.
4. For a guess of Π_1 , compute the second stage beliefs about the available borrower pool (equation 2.22). Compute the second stage uninformed lending cutoff, $A_2^U(\cdot)$.
5. Solve for the optimal π_2 . Call this value π_2^* .
6. Recompute the second stage informed lending cutoff, $\bar{\omega}_2$, and the cutoff type ω for the first stage profitability indicator function, $\Omega_1(\omega, z_1)$ assuming that z_1 is no longer in the information set (i.e. the banker has observed only z_{-1} and must

form an expectation about z_1 given the process for productivity). If solving for the equilibrium where banks fully internalize the effects of their actions on the borrower pool, compute Π_1 (equation 2.29) for each gridpoint of the range of π . If solving instead for the equilibrium where banks do not internalize the effects of their actions, allow Π_1 for each gridpoint of the range of π to be the guess of Π_1 from step 4.

7. Recompute the second stage beliefs about the available borrower pool (equation 2.22) for each gridpoint of the range of π (the degree of internalization of the friction plays its role here). Recompute $A_2^U(\cdot)$ for every realization of the second stage beliefs.
8. Using π_2^* and the second stage beliefs computed in step 6, compute $E_1[U_2(\psi_2, K_t, z_1)]$ (it will be a vector whose values are computed for each gridpoint of π).
9. Compute $U_1(\psi_1, K_t, z_{-1})$ for every value of π . The gridpoint of π that maximizes $U_1(\psi_1, K_t, z_{-1})$ is the optimal first stage lending intensity, which I denote by π_1^* .
10. If the conjectured guess of Π_1 in step 4 does not match π_1^* , then equilibrium condition (2.29) is violated. Update the guess in step 4 and repeat steps 4 through 9 until convergence according to the stopping criterion $|\Pi_1 - \pi_1^*| < 0.0001$.
11. Π_2 has not been needed so far because π_2^* does not depend on it (equation 2.32). Once π_1^* and π_2^* are obtained I impose $\Pi_2 = \pi_2^*$.
12. To check whether the model generates multiple equilibria, I solve for the optimal π_1^* by setting the initial guess of Π_1 in step 4 to the extreme values of both 0 and 1. I find that the optimal π_1^* computed under both starting values is the same, which suggests only one equilibrium exists.

A.2.2 SIMULATIONS

I simulate the model in response to productivity shocks by computing 10,000 different time series that are 8 periods long. Periods are connected via the productivity process (equation 2.2) and the transition equation for capital (equation 2.26). The level of capital in the model affects the levels of loans, borrowings, and output, but does not affect either choice of lending intensity, π_1 or π_2 . Therefore, because I study volatilities and correlations from the model, I normalize without loss of generality the initial capital, K_0 , of each time series to 1.

The model produces bank profits which are positive on average, so capital and thus loans and output grow over time. Hence, the model is non-stationary in these variables. I extract the cyclical components of capital, loans, and output in each time series by applying the HP-filter to the log of each variable, and then use these detrended data to compute volatilities and correlations.¹ I then take the average volatilities and correlations of all of the variables of interest over the 10,000 time series and report them in Tables 2.3-2.6.

¹I used the HP-filter with parameter value of 100 to detrend, which is the method I also used to compute the data moments.

APPENDIX B

APPENDIX FOR CHAPTER 3

B.1 MODEL DEFINITIONS

I define the delinquency rate in the model as the fraction of borrowers receiving credit who cannot repay the principal of the loan

$$\frac{\int_{M+\pi}^{\hat{\omega}} g(\omega) d\omega}{\int_{M+\pi}^{\infty} g(\omega) d\omega}, \quad (\text{B.1})$$

where $\hat{\omega}$ is defined as the borrower type who is just able to repay the loan principal

$$(1 - \kappa)y(\hat{\omega}, \frac{p_t^h}{p_{t-1}^h}, L_t) - L_t = 0. \quad (\text{B.2})$$

I define return on equity and return on assets as

$$ROE_t = \frac{K_{t+1} - K_t}{K_t}, \quad (\text{B.3})$$

$$ROA = \frac{K_{t+1} - K_t}{assets} = ROE * \frac{K_t}{assets}, \quad (\text{B.4})$$

with

$$assets = \int_M^{M+\pi} K_t g(\omega) d\omega + \int_{M+\pi}^{\infty} L_t g(\omega) d\omega. \quad (\text{B.5})$$

I define the investor credit-to-output ratio as total credit over total output

$$\frac{\int_{M+\pi}^{\infty} L_t g(\omega) d\omega}{\int_{M+\pi}^{\infty} y(\omega, \frac{p_t^h}{p_{t-1}^h}, L_t) g(\omega) d\omega}. \quad (\text{B.6})$$

I define the fraction of reserves in the representative bank's asset portfolio as total reserves divided by total assets

$$\frac{\int_M^{M+\pi} K_t g(\omega) d\omega}{assets}. \quad (\text{B.7})$$

Lastly, I define regulator losses in equation (3.23).

B.2 NUMERICAL ALGORITHM

1. Initialize the prior and level of capital. I set the initial prior, p_t , to its invariant distribution value of 40%. Next, I normalize starting capital, K_0 , to one. This assumption is without loss of generality because in the model it is the leverage ratio, and not the absolute level of capital, which affects the choice of lending standards, π_t .
2. Compute expected house price growth, $E_{t-1} \left[\frac{p_t^h}{p_{t-1}^h} \right]$, as described in equation (3.7).
3. Compute the optimal choice of lending standards using equations (3.19)–(3.21).
4. Draw a house price growth shock from the stochastic process described in Section 3.3.2.¹

¹For the purposes of calibrating the model and reporting comparative statics, the house price growth shock was set to its long-run mean.

5. Using the optimal π_t from step 3 and the value of the house price growth shock, compute the model values described in Appendix B.1 and next period's starting capital (equation 3.13).²
6. Use the house price growth shock to compute banks' updated beliefs (equations 3.4 – 3.6). Repeat steps 2-6.

²Because capital grows over time, model variables including output, credit and bank borrowings are non-stationary. However, because the bank's objective function is linear in capital, the level of capital does not affect the choice of lending standards or the ratios computed in Appendix B.1.

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