

Overlending and Macroprudential Tools*

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Abstract

This paper is a quantitative study of two frictions that generate banks' underinvestment in screening borrowers and, thus, overlending: 1) Limited liability, and 2) Banks failing to internalize that their credit decisions alter the pool of borrowers faced by other banks. The resulting lax lending standards overexpose banks to negative economic shocks and amplify the effects of economic fluctuations. They generate excessive volatility in credit, banks' capital and output. We study a calibrated model whose predictions concerning the quantity and quality of credit are in line with recent U.S. business cycles. Quantitatively, limited liability is the friction that generates laxer lending standards. It induces 27% excess volatility in output relative to 8% from the other friction. Then we study three policy tools: capital requirements and taxes on banks' lending and borrowings. The three tools encourage banks to screen more and should be state-contingent because the frictions vary with macroeconomic conditions. In quantitative terms, we find that taxes are better tools than capital requirements because they do not reduce credit going to the more productive agents.

Keywords: Lending Standards, Limited Liability, Capital Requirements, Bank Taxation, Overlending.

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"Bank management in Ireland, like many banks elsewhere in the world, had forgotten the very nature of credit. Providing credit is not a sale of bank services; it is the acquisition of a risky asset. The appropriate prudential focus of such a transaction is therefore limiting and mitigating risk (or, at the very least, understanding the real risk and pricing it accordingly) rather than expanding sales. This apparent inability, some might say unwillingness, of Irish banks to remember this basic principle of banking was a major cause of the banking crisis in Ireland. This problem was further exacerbated as many banks appear to have emphasized and valued loan sales skills above risk and credit analysis skills." Commission of Investigation into the Banking Sector. The Minister for Finance of Ireland, March 2011.

1 Introduction

Given the size of the recent financial crisis, there is a large debate on how to develop macroprudential regulations to avoid future crises. There seems to be a consensus that lax lending standards was one of the causes of the crisis (see for example Acharya and Richardson 2009, Allen and Carletti 2009, Rajan 2010 and Taylor 2009). In this paper we do a quantitative study of two frictions that generate lax lending standards: 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. We show that both frictions lead banks to devote too little resources to screening their borrowers relative to selling them credit. That is, banks give too much low quality credit, thus they "overlend". Overlending amplifies the effects of economic shocks and induces excessive volatility in banks' capital and output. In quantitative terms, we find limited liability to be the larger friction. It generates laxer lending standards and induces 27% extra output volatility (versus 8% for the other friction). To address the frictions, we study three policy tools: capital requirements and taxes on banks' lending and borrowings.¹ The three tools encourage banks to screen more although through different channels. Additionally, the tools should be state-contingent because the frictions' effects vary with both bank funding costs and borrowers' productivity. In our model taxes are the best policy tool because they do not reduce the size of the loans going to the more productive agents.

Limited liability has been widely recognized as a possible cause of excessive risk taking if the parties sustaining the potential losses are unable to negotiate for compensation before or while the risk-taking decision is made (Sinn 2001 surveys the literature). Under limited liability the probability distribution of income is truncated, and negative returns to bank owners are limited to the amount of paid-in capital.

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.

The second friction that we study has been recently theorized by Hachem (2012) and it is motivated by evidence such as Shaffer (1998), who documents that loan applicants rejected by one bank apply at another bank, systematically worsening the pool of applicants faced by all banks. Hachem shows that if three conditions are met, then in a competitive equilibrium banks screen too little (generating excessive low quality lending) relative to a social planner 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 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.

Our model integrates both frictions. There are banks and firms. Firms need credit to produce and borrow from the banks. The production function of a firm depends on idiosyncratic productivity (which is constant over time) and an aggregate productivity shock (which fluctuates over time). Firms are heterogeneous in idiosyncratic productivity and this is private information. Banks can only observe it with some positive probability if they spend resources on screening, or once the loan matures. We study two banking decisions: how many resources banks allocate to screening (which we will call lending standards), and when banks give credit to a borrower. To simplify we assume that firms' behavior is mechanical: they try to borrow as much as they can to produce a single good. The interesting action happens on the bank side.

Each period in the model has two stages, and each stage is divided in two (we denote them as 1a, 1b, 2a and 2b). In stage 1a banks are endowed with a fixed amount of resources (e.g. time or employees) that they can use to look for borrowers or to screen them. If banks screen less, 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 is a convenient modelling trick we copy from Hachem (2012) but the results of the model would also hold if alternatively we assume that the cost of screening is in terms of the numeraire and banks face a budget constraint. The trick 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.² 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.

In stage 1b of the model banks that successfully found a borrower may or may not know the idiosyncratic productivity of that borrower. In either case the bank has to decide whether and

²Heider and Inderst (2012) provide support for modelling 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 who incentivize their employees to attract more borrowers must pay a cost in terms of gathering soft information potentially useful for screening purposes.

how much credit to give to the 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 over the two stages. Loan size is given by the amount of bank capital plus the bank's borrowings subject to a capital requirement constraint. Unmatched banks and those who matched but did not give credit can lend their capital in the money market at an exogenous rate.

At the end of this first stage the aggregate shock is realized, and borrowers produce and pay the banks. At that moment all banks learn the idiosyncratic productivity of their borrowers. If the borrower was bad, the bank makes losses and dies. Because of limited liability, the bank cannot bear losses larger than its capital. Bad customers are returned to the pool of borrowers and good ones can be retained for the next stage.

In stage 2a, matched banks with retained good borrowers renew their loans. Banks unmatched from stage 1a and those separated in stage 1b face again the decision problem of stage 1a. However, now the quality of the pool of available borrowers has changed because some good borrowers are already matched. Moreover, expectations about the aggregate shock may have also changed after the stage 1 shock. Stage 2b repeats stage 1b after a new aggregate productivity shock. At the end of stage 2b all banks and borrowers separate and a new period starts.

We simulate the model as a sequence of periods each one involving these four steps. Periods are connected because the amount of capital is inherited from the retained earnings of the previous one, and any aggregate productivity shock depends on the previous one. There are two sources of endogenous volatility in the economy: changes in lending standards and changes in bank capital over periods.

Both frictions push for lax lending standards and overlending. 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) individual banks at stage 1a do not internalize that by giving credit and retaining the good borrowers, they lower the quality of the pool of borrowers at stage 2a, thus they allocate excessive resources to sales (too little screening) relative to a planner 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.

We calibrate our 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 we 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 we document in Section 4.1. Periods of rapid loan growth are followed by periods of higher delinquency rates.³ The model is quite successful at matching this pattern.

The model matches the data because when banks expect high productivity, they lower screening intensity to try to give more credit. This results in a credit boom that is accompanied by more uninformed credit and, if a subsequent shock turns out to be worse than expected, this increases bank defaults. Moreover, the model also replicates quite well the business cycle volatilities of the quantity and quality of bank credit.

We use our calibrated model to do a quantitative comparison of the frictions. We find limited liability to be the more dangerous friction. In simulations of the calibrated model, bank capital and output are 27% more volatile when there is limited liability and 8% more volatile when there is lack of internalization.

We 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 also should change.

The three policy tools that we 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. The tax on lending makes lending less profitable by reducing the revenue from a borrower, and the tax on banks' borrowings works by increasing the cost of funding a loan. Capital requirements operate by increasing banks' "skin in the game" (a larger fraction of the losses are borne by the bankers), and by lowering leverage ratios and loan profits, which makes matching less desirable relative to screening (given that

³This fact also holds for many other countries (for example, see Elekdag and Wu 2011, Igan and Pinheiro 2011 or Mendoza and Terrones 2008).

banks cannot raise capital, their loans are smaller when capital requirements increase and bank leverage is reduced, then banks' profits from making a loan go down).⁴ The main difference between these channels is that the taxes alter the profitability per unit of credit while the capital requirements do not. In this sense, taxes are akin to a scalpel whereas capital requirements are a more blunt policy tool. Or, comparing with trade regulations, capital requirements work more as import quotas (restrict quantities) while taxes work as import tariffs (alter prices). 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. That is, in quantitative terms we find that the taxes are better tools than the capital requirements because they reduce credit less to the more productive agents of the economy.

This paper contributes to the literature on four dimensions. First, we contribute to the nascent 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 those models, in fact it is common to work with small open economy frameworks in which lenders are unmodelled. 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. Our work complements this literature by taking the opposite approach. We focus on frictions that operate via the lenders, thus "overlending", and in our 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. We differ in the frictions studied.

Second, we 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.⁵ 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, we 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

⁴For very high capital requirements the banks cannot borrow thus the tax on borrowings would be useless.

⁵For 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).

(2010) or Perotti and Suarez (2011). IMF (2010) surveys existing work and recent policy proposals.

Fourth, we contribute to the banking literature from a macro view. We show that a model where meeting with borrowers implies an opportunity cost in terms of screening them can match the empirical patterns of the quality and quantity of credit over the business cycle.

The structure of the paper is the following: Section 2 presents the model and Section 3 introduces the value functions. Section 4 documents some facts about the quality and the quantity of U.S. credit, calibrates the model and discusses its quantitative properties. Section 5 studies the frictions and the excessive volatility they generate. Section 6 discusses the three policy tools. Section 7 concludes. The Appendix describes the data and the numerical algorithm.

2 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 with each stage divided in two substages. To generate time series we repeat the multi-stage problem, connecting the periods by the laws of motion for banks' capital and aggregate productivity.

2.1 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.⁶ They have no storage technology and no endowment, so they must borrow from banks in order to produce. Their production technology is

$$y(\omega, z_t, L_t) = \theta \omega^\alpha z_t L_t \quad (1)$$

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 we model as a log-normal AR(1) process:

$$\log z_t = \rho_z \log z_{t-1} + \varepsilon_{z,t} \quad (2)$$

$$\varepsilon_{z,t} \sim N[0, \sigma_z^2] \quad (3)$$

⁶This 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.

We make a few simplifying assumptions. First, we 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). It is a reduced form approach to how the surplus from a lending relationship is split between the lender and the borrower. Second, in the Labor-Search literature it is customary to have a parameter that controls the bargaining power of the firms versus the workers. Here we use the same assumption and assume the parameter $\kappa \geq 0$ controls the bargaining power of the firms versus the banks. That is, the surplus of a lending relationship, $y(\omega, z_t, L_t)$, is split 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 our focus will be the quantity of credit instead of the price of credit. Third, to ensure that all firms seek the maximum financing, we assume that the firm's fraction κ cannot be seized by the banks for loan repayment. That is, from the firm's side it is optimal to always apply for the maximum amount of credit available because the firm will always receive share κ of the surplus.

2.2 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 2.5.⁷ Since we abstract from strategic interactions between banks and all banks are alike, we 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. We divide each stage into two substages that we 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 matters because 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

⁷This assumption is without loss of generality because, as we show in Section 3, the value functions are linear in bank capital and the level of capital does not matter for the screening decision nor for the decision to give credit.

making decisions. We will discuss the borrower distributions in the next subsection.

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

Insert Figure 1 about here

1a) In stage 1a, the bank has to allocate one unit of resources (for example employees) between attracting customers or screening them. There is a tradeoff between these activities. We 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 we 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 $\pi_{1t}(1 - \pi_{1t})$, we call these bankers "informed"; 2) become matched with a borrower and not learn that borrower's type with probability π_{1t}^2 , we call these banks "uninformed"; or 3) remain unmatched with probability $(1 - \pi_{1t})$. If we 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 .⁸ Banks that successfully matched with a borrower must decide whether to lend to their borrower or to invest 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. We 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 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 .⁹

⁸Since banks are risk neutral it does not matter if we assume that this return is safe or risky. Banks make decisions based on expected values.

⁹Assuming 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.

Banks are subject to a capital requirement, $\gamma \geq 0$, such that

$$L_t = B_t + K_t \quad (4)$$

$$K_t \geq \gamma L_t \quad (5)$$

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, we use the following indicator function that takes the value one when a bank is profitable in stage 1

$$\Omega_1(\omega, z_1) = \begin{cases} 0 & \text{if } (1 - \kappa)y(\omega, z_1, L_t) \leq (1 + i_b)B_t \\ 1 & \text{if } (1 - \kappa)y(\omega, z_1, L_t) > (1 + i_b)B_t \end{cases} \quad (6)$$

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. 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 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 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 we describe in Section 2.4, 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, we assume

that profits or losses are integrated into the aggregate capital stock and that this is equally distributed among the continuum of banks. Section 2.5 describes the law of motion for bank capital. New banks enter so that we again have mass one of banks when a new period starts.

We 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 2.5, 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, we introduce an adjustment cost $\frac{c}{2} (\pi_{it} - \pi^{ss})^2 K_t$, $i = 1, 2$, which is commonplace in macro models. We 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.

To simplify the notation in the rest of the model exposition, for variables that do not relate to different periods we will drop the t subscript. Thus, instead of using the π_{1t} notation to denote stage 1 of period t , we will just write π_1 . It is important to note that with this notation we do not mean that all periods are alike, that is, we are not assuming $\pi_{1t} = \pi_1 \forall t$. Since K_t does not change across the stages of period t , we 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 . We 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 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:

$$L_t = \frac{K_t}{\gamma} \tag{7}$$

$$B_t = \left(\frac{1}{\gamma} - 1 \right) K_t \tag{8}$$

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 our model can match the empirical fact documented among others by Allen et al. (2011) that for U.S. commercial banks

the average capital to asset ratio is twice the 4% that capital regulation dictated. Aiyar et al. (2012), Alfonsi 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 undertake 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

$$R_1(\omega, z_{-1}, L_t) \equiv \int_0^{\infty} (1 - \kappa) y(\omega, z_1, L_t) f(z_1 | z_{-1}) dz_1 \quad (9)$$

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, $(1 + i_b)K_t$. We 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 $\bar{\omega}_1$

$$R_1(\bar{\omega}_1, z_{-1}, L_t) = (1 + i_b)(B_t + K_t) \quad (10)$$

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

$$A_1(\omega, z_{-1}) = \begin{cases} 0 & \text{if } \omega < \bar{\omega}_1 \\ 1 & \text{if } \omega \geq \bar{\omega}_1 \end{cases} \quad (11)$$

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

$$R_2(\bar{\omega}_2, z_1, L_t) = (1 + i_b)(B_t + K_t) \quad (12)$$

where

$$R_2(\omega_2, z_1, L_t) \equiv \int_0^\infty (1 - \kappa)y(\omega_2, z_2, L_t)f(z_2|z_1)dz_2 \quad (13)$$

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

$$A_2(\omega, z_1) = \begin{cases} 0 & \text{if } \omega < \bar{\omega}_2 \\ 1 & \text{if } \omega \geq \bar{\omega}_2 \end{cases} \quad (14)$$

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 we 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

$$R_1^U(\psi_1(\cdot), z_{-1}, L_t) \equiv \int_0^1 \int_0^\infty (1 - \kappa)y(\omega, z_1, L_t)f(z_1|z_{-1})\psi_1(\omega)d\omega dz_1 \quad (15)$$

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. We keep track of uninformed banks lending using the following indicator function:

$$A_1^U(\psi_1(\cdot), z_{-1}) = \begin{cases} 0 & \text{if } R_1^U(\psi_1(\cdot), z_{-1}, L_t) < (1 + i_b)(B_t + K_t) \\ 1 & \text{if } R_1^U(\psi_1(\cdot), z_{-1}, L_t) \geq (1 + i_b)(B_t + K_t) \end{cases} \quad (16)$$

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 (we define it in the next subsection), then the expected revenue from uninformed lending in stage

2 is

$$R_2^U(\psi_2(\cdot), z_1, L_t) \equiv \int_0^1 \int_0^\infty (1 - \kappa) y(\omega, z_2, L_t) f(z_2|z_1) \psi_2(\omega) dz_2 d\omega \quad (17)$$

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

$$A_2^U(\psi_2(\cdot), z_1) = \begin{cases} 0 & \text{if } R_2^U(\psi_2(\cdot), z_1, L_t) < (1 + i_b)(B_t + K_t) \\ 1 & \text{if } R_2^U(\psi_2(\cdot), z_1, L_t) \geq (1 + i_b)(B_t + K_t) \end{cases} \quad (18)$$

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 (7) and (8) with the decision rules discussed above, we 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.

2.4 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 2.6 we 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

$$\psi_1(\omega) = 1. \quad (19)$$

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:

$$\lambda_1(\omega) = \Pi_1(1 - \Pi_1)A_1(\omega, z_{-1}) \quad (20)$$

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:

$$\phi_1(\omega) = \Pi_1^2 A_1^U(\psi_1(\cdot), z_{-1}) \quad (21)$$

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

$$\psi_2(\omega) = \frac{1 - A_2(\omega, z_1)\Omega_1(\omega, z_1)(1 - \mu)(\lambda_1(\omega) + \phi_1(\omega))}{\int_0^1 [1 - A_2(\omega, z_1)\Omega_1(\omega, z_1)(1 - \mu)(\lambda_1(\omega) + \phi_1(\omega))] d\omega} \quad (22)$$

where the numerator takes into account the four reasons why a borrower is available in stage 2a: 1) if she did not match in stage 1a or she did not receive credit in stage 1b, $\lambda_1(\omega) = 0 = \phi_1(\omega)$; 2) if she was found unprofitable at the start of stage 2a and hence her lending bank defaulted, $\Omega_1(\omega, z_1) = 0$; 3) if she was profitable but hit by a separation shock with probability μ ; or 4) if she was profitable but she is not expected to be profitable in the second stage, $A_2(\omega, z_1) = 0$. 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, we 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

$$\eta_2 = 1 - \int_0^1 [(1 - \Omega_1(\omega, z_1)) + A_2(\omega, z_1)\Omega_1(\omega, z_1)(1 - \mu)] (\lambda_1(\omega) + \phi_1(\omega)) d\omega. \quad (23)$$

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:

$$\lambda_2(\omega) = A_2(\omega, z_1)(1 - \mu)\Omega_1(\omega, z_1)(\lambda_1(\omega) + \phi_1(\omega)) + \psi_2(\omega)\eta_2\Pi_2(1 - \Pi_2)A_2(\omega, z_1) \quad (24)$$

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, $A_2(\omega, z_1) = 1$. We are 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 (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:

$$\phi_2(\omega) = \psi_2(\omega)\eta_2\Pi_2^2 A_2^U(\psi_2(\cdot), z_1) \quad (25)$$

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, $A_2^U(\psi_2(\cdot), z_1) = 1$.

2.5 Profits of the Banking Sector

We 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:

$$K_{t+1} = K_{t+1}^1 + K_{t+1}^2 \quad (26)$$

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

$$K_{t+1}^1 = \int_0^1 \left\{ (\max \{0, (1 - \kappa)y(\omega, z_1, L_t) - (1 + i_b)B_t\}) [\lambda_1(\omega) + \phi_1(\omega)] + (1 + i_b) K_t (1 - \lambda_1(\omega) - \phi_1(\omega)) - \frac{\epsilon}{2} (\pi_1 - \pi_1^{ss})^2 K_t \right\} d\omega \quad (27)$$

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. 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

$$K_{t+1}^2 = \int_0^1 \left\{ \begin{aligned} & (\max \{0, (1 - \kappa)y(\omega, z_2, L_t) - (1 + i_b)B_t\}) [\lambda_2(\omega) + \phi_2(\omega)] + \\ & + (1 + i_b) K_t \eta_2 [1 - \psi_2(\omega) \Pi_2 [\Pi_2 A_2^U(\psi_2(\cdot), z_1) + (1 - \Pi_2) A_2(\omega, z_1)]] + \\ & - \eta_2 \left[\frac{c}{2} (\pi_2 - \pi_2^{ss})^2 K_t \right] \end{aligned} \right\} d\omega \quad (28)$$

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 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.

2.6 Equilibrium

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

$$\Pi_{it} = \pi_{it} \quad \forall t, i = 1, 2 \quad (29)$$

We will compare two cases. First, banks internalize that their behavior affects the quality of the pool of borrowers faced by other lenders. That is, banks incorporate (29) into their decision problem. Thus there is no friction as banks correctly internalize that their choice of lending intensity π alters Π . Second, banks do not internalize the effect of their choice of π on Π , for example because they are small banks and think their actions are not significant enough to affect the quality of the borrower's pool. In equilibrium (29) holds, but since banks do not integrate (29) into their decision problem the friction is at its maximum.

We define an equilibrium in the model when, for exogenous cost of funds i_b and productivity z that evolves according to (2) and (3), firms and banks optimize and (29) holds. The next section describes the value functions and the appendix 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 (4) and to the capital requirement (5). Given the capital inherited from the previous period, the capital for the following period will be determined according to equations (26) – (28).

3 Bank's Value Functions

A bank can be in 3 different situations: 1) unmatched with a borrower, in which case we 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.

3.1 Unmatched Bank

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

$$U_1(\psi_1(\cdot), K_t, z_{-1}) = \max_{0 \leq \pi_1 \leq 1} \left\{ \pi_1^2 N_1(\psi_1(\cdot), K_t, z_{-1}) + \pi_1(1 - \pi_1) \int_0^1 J_1(\omega, K_t, z_{-1}) \psi_1(\omega) d\omega + \right. \\ \left. + (1 - \pi_1) [(1 + i_b) K_t + E_1(U_2(\psi_2(\cdot), K_t, z_1))] - \frac{c}{2} (\pi_1 - \pi_1^{ss})^2 K_t \right\} \quad (30)$$

with the expectation

$$E_1(U_2(\psi_2(\cdot), K_t, z_1)) = \int_0^\infty U_2(\psi_2(\cdot), K_t, z_1) f(z_2|z_{-1}) dz_2 \quad (31)$$

The first term of (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:

$$\begin{aligned}
U_2(\psi_2(\cdot), K_t, z_1) = & \max_{0 \leq \pi_2 \leq 1} \{ \pi_2^2 N_2(\psi_2(\cdot), K_t, z_1) + \\
& + \pi_2(1 - \pi_2) \int_0^1 J_2(\omega, K_t, z_1) \psi_2(\omega) d\omega + \\
& + (1 - \pi_2) (1 + i_b) K_t - \frac{c}{2} (\pi_2 - \pi_2^{ss})^2 K_t \}. \tag{32}
\end{aligned}$$

This function is similar to equation (30) with the difference banks know that their cohort dies at the end of the second stage.

3.2 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:

$$\begin{aligned}
J_1(\omega, K_t, z_{-1}) = & \max_{A_1(\omega, z_{-1}) \in \{0,1\}} \{ (1 - A_1(\omega, z_{-1})) [(1 + i_b) K_t + E_1(U_2(\psi_2(\cdot), K_t, z_1))] + \\
& + A_1(\omega, z_{-1}) \left[\int_0^\infty (\max \{0, (1 - \kappa)y(\omega, z_1, L_t) - (1 + i_b)B_t\}) f(z_1|z_{-1}) dz_1 + \right. \\
& \left. + \int_0^\infty \Omega_1(\omega, z_1) \left(\begin{array}{c} \mu E_1[U_2(\psi_2(\cdot), K_t, z_1)] \\ + (1 - \mu) E_1[J_2(\omega, K_t, z_1)] \end{array} \right) f(z_1|z_{-1}) dz_1 \right] \} \tag{33}
\end{aligned}$$

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 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 (31).

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

$$J_2(\omega, K_t, z_1) = \max_{A_2(\omega, z_1) \in \{0,1\}} \left\{ (1 - A_2(\omega, z_1)) (1 + i_b) K_t + \right. \\ \left. + A_2(\omega, z_1) \left[\int_0^\infty (\max \{0, (1 - \kappa)y(\omega, z_2, L_t) - (1 + i_b)B_t\}) f(z_2|z_1) dz_2 \right] \right\} \quad (34)$$

where the difference relative to (33) is that banks know that their cohort dies at the end of the second stage.

3.3 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:

$$N_1(\psi_1(\cdot), K^t, z_{-1}) = \max_{A_1^U(\psi_1(\cdot), z_{-1}) \in \{0,1\}} \left\{ (1 - A_1^U(\psi_1(\cdot), z_{-1})) [(1 + i_b) K_t + E_1[U_2(\psi_2(\cdot), K_t, z_1)]] + \right. \\ \left. + A_1^U(\psi_1(\cdot), z_{-1}) \left[\int_0^1 \int_0^\infty (\max \{0, (1 - \kappa)y(\omega, z_1, L_t) - (1 + i_b)B_t\}) f(z_1|z_{-1}) \psi_1(\omega) dz_1 d\omega + \right. \right. \\ \left. \left. + \int_0^1 \int_0^\infty \Omega_1(\omega, z_1) \left(\frac{\mu E_1[U_2(\psi_2(\cdot), K_t, z_1)]}{+(1 - \mu)E_1[J_2(\omega, K_t, z_1)]} \right) f(z_1|z_{-1}) \psi_1(\omega) dz_1 d\omega \right] \right\} \quad (35)$$

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

$$N_2(\psi_2(\cdot), K_t, z_1) = \max_{A_2^U(\psi_2(\cdot), z_1) \in \{0,1\}} \left\{ (1 - A_2^U(\psi_2(\cdot), z_1)) (1 + i_b) K_t + \right. \\ \left. + A_2^U(\psi_2(\cdot), z_1) \left\{ \int_0^1 \int_0^\infty (\max \{0, (1 - \kappa)y(\omega, z_2, L_t) - (1 + i_b)B_t\}) f(z_2|z_1) \psi_2(\omega) dz_2 d\omega \right\} \right\} \quad (36)$$

where the difference relative to (35) is that banks know that their cohort dies at the end of the second stage.

4 Empirical Facts and Quantitative Properties of the Model

In this section, we document business cycle facts about the quality and quantity of bank credit in the U.S. Then we calibrate our 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. We will use this calibrated model in the following sections of the paper.

4.1 Some Facts about the Quality and Quantity of Credit

Our data sample period is restricted to the period in which all of our variables of interest are available, so we use annual data from 1987-2010. We deflate nominal variables using the GDP deflator.¹⁰ The sources for the data are listed in the Appendix.

Figure 2 focuses on 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.

Insert Figure 2 about here

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. Bank credit (business or aggregate) is also 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 1 and 4 document numerically the patterns of

¹⁰To detrend the series we 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 we use the 6.25 parameter proposed by Ravn and Uhlig (2002).

Figure 2.

Insert Table 1 about here

4.2 Calibration

Table 2 summarizes our parameterization. We 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. Our calibration targets the model when productivity is at its long run mean. We calibrate to the case in which banks do not internalize the credit friction.

Insert Table 2 about here

We 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), we 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 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.¹¹

We 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 our sample period. This level of equity is above the benchmark capital requirement we calibrate below and the model is able to target it because not all banks operate with a binding capital requirement constraint.

¹¹In 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:

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

Initial capital is a scale variable on the objective function, so it does not affect the choice of either π_1 or π_2 , just the levels of output, loans, and borrowings. Thus without loss of generality we normalize it to 1 and let equation (26) govern its dynamics. We assume a capital requirement of 4%, which was the Tier 1 capital requirement under Basel I. This was the regulation in effect over most of our sample period.

We follow Bianchi and Mendoza (2010) to calibrate the TFP process, adjusting the persistence, ρ_z , and variance of the shock process, σ_z^2 , to a semestral frequency since we have two shocks per period.¹²

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.

4.3 Quantitative Properties of the Model

To simulate business cycles we 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. We discuss the methodology behind the simulations further in the Appendix. We think of the model as a representative agent of the banking system.

Table 3 reports the correlation of the quantity of credit with the quality of credit from the model. We find that the model generates measures of quality of credit 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.

Insert Table 3 about here

Table 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

¹²In our setup, the mean of the TFP process is normalized to equal 1. Calibrating this mean would be equivalent to changing our calibration of θ .

(26), and the choices of lending intensities and the pivotal borrowers. The relative volatilities from the model also resemble the volatilities relative to industrial production.

Insert Table 4 about here

5 Overlending and Excessive Volatility

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

5.1 Overlending

Figures 3 and 4 report comparative statics exercises to illustrate the effects of the frictions. The panels on the top of Figure 3 plot the screening intensity at stage 1a for the models with and without each of the frictions as a function of aggregate productivity. The panels on the bottom plot the differences between the model with the friction and the model without it. 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 4 redoes figure 3 but as a function of the cost of banks' borrowings.

Insert Figure 3 about here

Insert Figure 4 about here

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 $\pi = 0.5$. We 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. This 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 a larger problem, i.e., the gap between screening when there is no friction and when there is an 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.

5.2 Excessive Volatility

In this subsection we 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 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.

Insert Figure 5 about here

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 our model requires credit in order to produce, all variables of an economy with frictions are more volatile than in an economy without them. Table 5 shows this result.

Insert Table 5 about here

When we examine the impact of each friction individually in Table 6, we 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 3 and 4, the limited liability friction generates more uninformed, low quality credit than does the other friction, so banks are more exposed to economic shocks.

Insert Table 6 about here

6 Policy Tools

In this section we 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 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, we consider a tax on banks' borrowings, τ_b , such that the after tax cost for banks of external financing is $(1 + \tau_b)(1 + i_b)B_t$. This 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 6 we study how the policy tools affect total credit. We 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.

Insert Figure 6 about here

In all of the plots of Figure 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 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.¹³ We thus see a smooth decline in the level of total credit with this tool.

In Table 7 we compare the policy tools. For our benchmark parameterization and no shocks, we compute the change in capital requirements and in taxes needed to lower the amount of total credit by 5%. We find that capital requirements should increase from our benchmark of 4% to 4.17%. This 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%.

Insert Table 7 about here

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.

This distinction can again be seen when we examine the effects of the policies on the types of credit available in the economy. We find that the taxes are better at getting rid of the type of lower-quality credit we do not want (the uninformed credit) without reducing the higher-quality credit we 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.

7 Conclusions

We 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 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, we find

¹³Similarly, 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.

limited liability to be the larger friction.

Our quantitative model displays patterns very similar to the empirical regularities of the quantity and quality of U.S. bank credit documented in Section 4.1. For example, the model replicates that periods of high credit volume are followed by increases in loan losses because banks give too much low-quality credit during credit booms. The model also matches well the volatilities of banking variables.

Through time series simulations and impulse responses, we showed that the frictions generate excessive volatility in the business cycles of banking variables and aggregate output. In our calibrated model, output and credit would be 35% less volatile if banks correctly internalized the frictions.

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, we 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.

Our model lacks a well defined welfare criterion to evaluate the optimality of reducing the frictions. That is, the model does not address why excessive volatility is bad. A model with consumption smoothing agents would microfound this welfare function. We leave these extensions for future research.

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Appendix: Data and Computation

Data Sources

Data Sources: 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).

Computation Procedure

Solution Algorithm

Every period is a two-stage model, and we solve backwards for the optimal π_1 and π_2 . That is, in the second stage, we 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 2.6 we 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 . We 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), 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 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 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 22) for each gridpoint of the range of π (the degree of internalization of the friction plays its role here). Recompute $A_2^U(.)$ 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 we denote by π_1^* .
10. If the conjectured guess of Π_1 in step 4 does not match π_1^* , then equilibrium condition (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 32). Once π_1^* and π_2^* are obtained we impose $\Pi_2 = \pi_2^*$.
12. To check whether the model generates multiple equilibria, we 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. We find that the optimal π_1^* computed under both starting values is the same, which suggests only one equilibrium exists.

Simulations

We 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) and the transition equation for capital (equation 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 we study volatilities and correlations from the model, we 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, our model is non-stationary. We 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.¹⁴ We then take the average volatilities and correlations of all of our variables of interest over the 10,000 time series and report them in Tables 3-6.

¹⁴We used the HP-filter with parameter value of 100 that we used to compute the data moments.

Table 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 in the Appendix).										
Data detrended with the Hodrick-Prescott filter with smoothing parameter 100.										

Table 2: Calibrated Parameters

Parameter	Value	Target
θ	10.7	Ratio of capital to loans of 8.57% as in FRED, in model: 8.53% if no shocks
α	0.03	FRED's series of charge-off rates on Business Loans: 0.91%, in model: 0.56% if no shocks
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% if no shocks
κ	0.9	Average return on equity of 20% as in ECB (2010), in model: 25.1% if no shocks
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

Table 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 the Appendix.					

Table 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. Model simulated as discussed in the Appendix.			

Table 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 the Appendix.			

Table 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 the Appendix.		

Table 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%.			

Figures

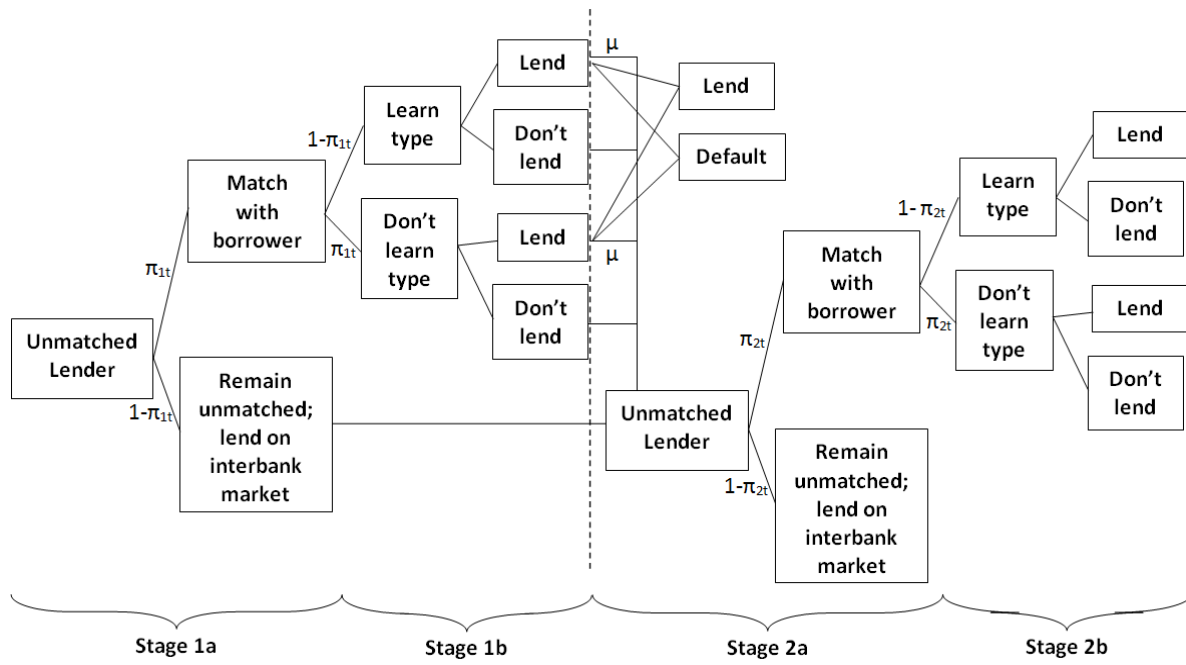


Figure 1: Summary of Bank's Problem in Period t .

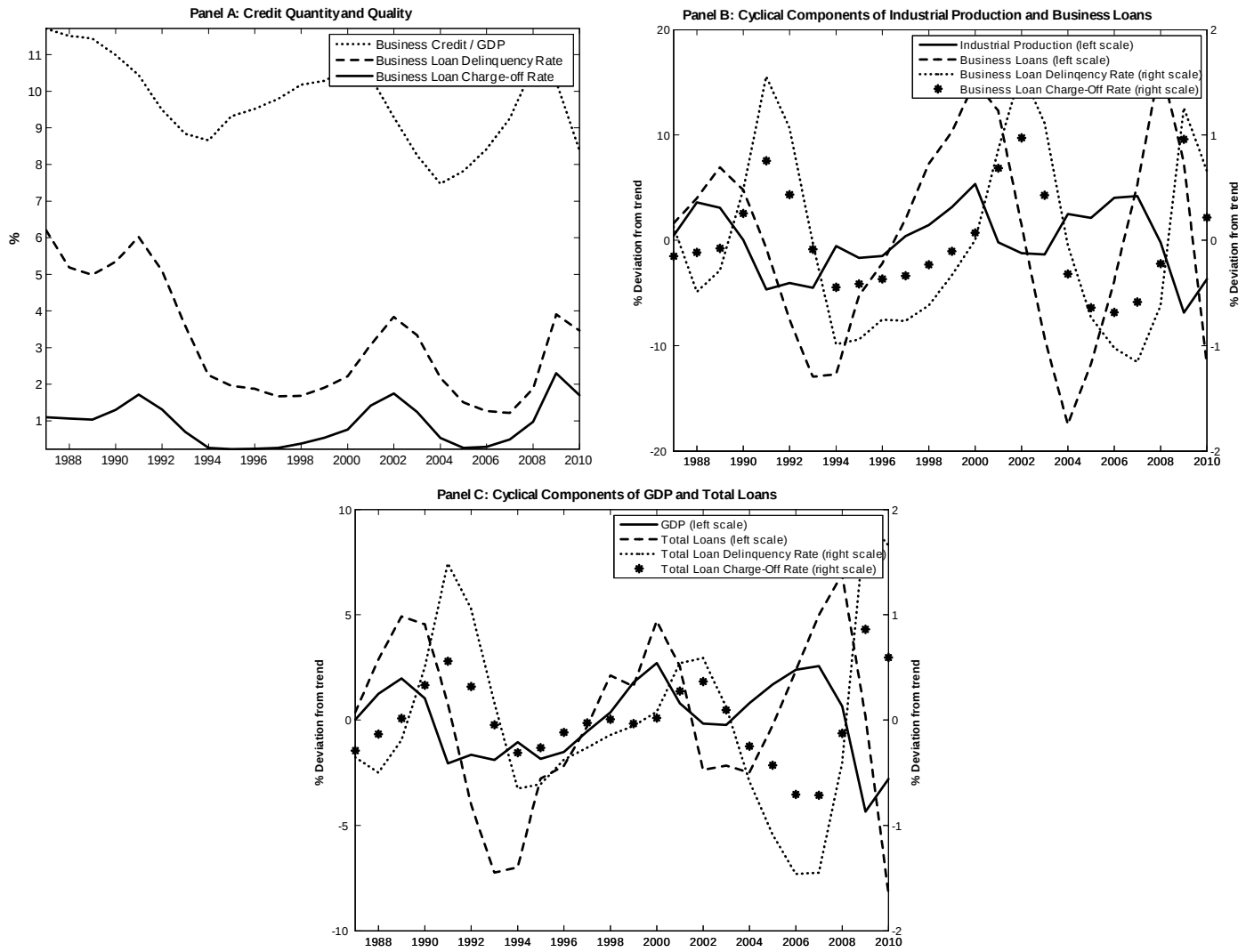


Figure 2: Facts about the Quantity and Quality of Credit. Panel A plots the business credit to GDP ratio against the delinquency rate and the charge-off rates on commercial and industrial loans. Panel B plots the cyclical component of industrial production, the quantity of business credit, the delinquency 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.

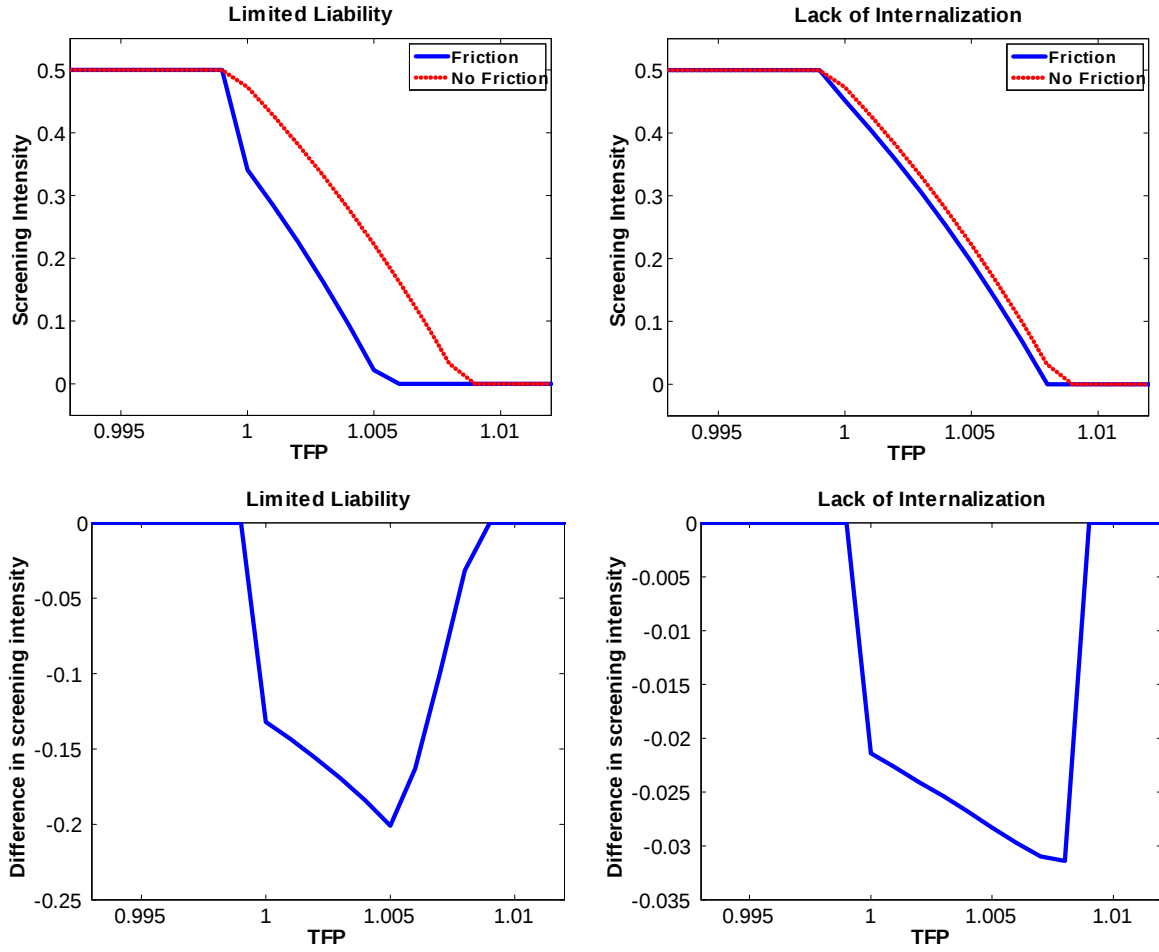


Figure 3: Screening Intensity as a Function of Firm's TFP. The panels on the top plot the screening intensity at stage 1a for the models with and without frictions as a function of firms' TFP. The panels on the bottom plot their differences. The panels on the left focus on limited liability as the unique friction. The panels on the right focus on lack of internalization of the effects on the quality of the borrower's pool.

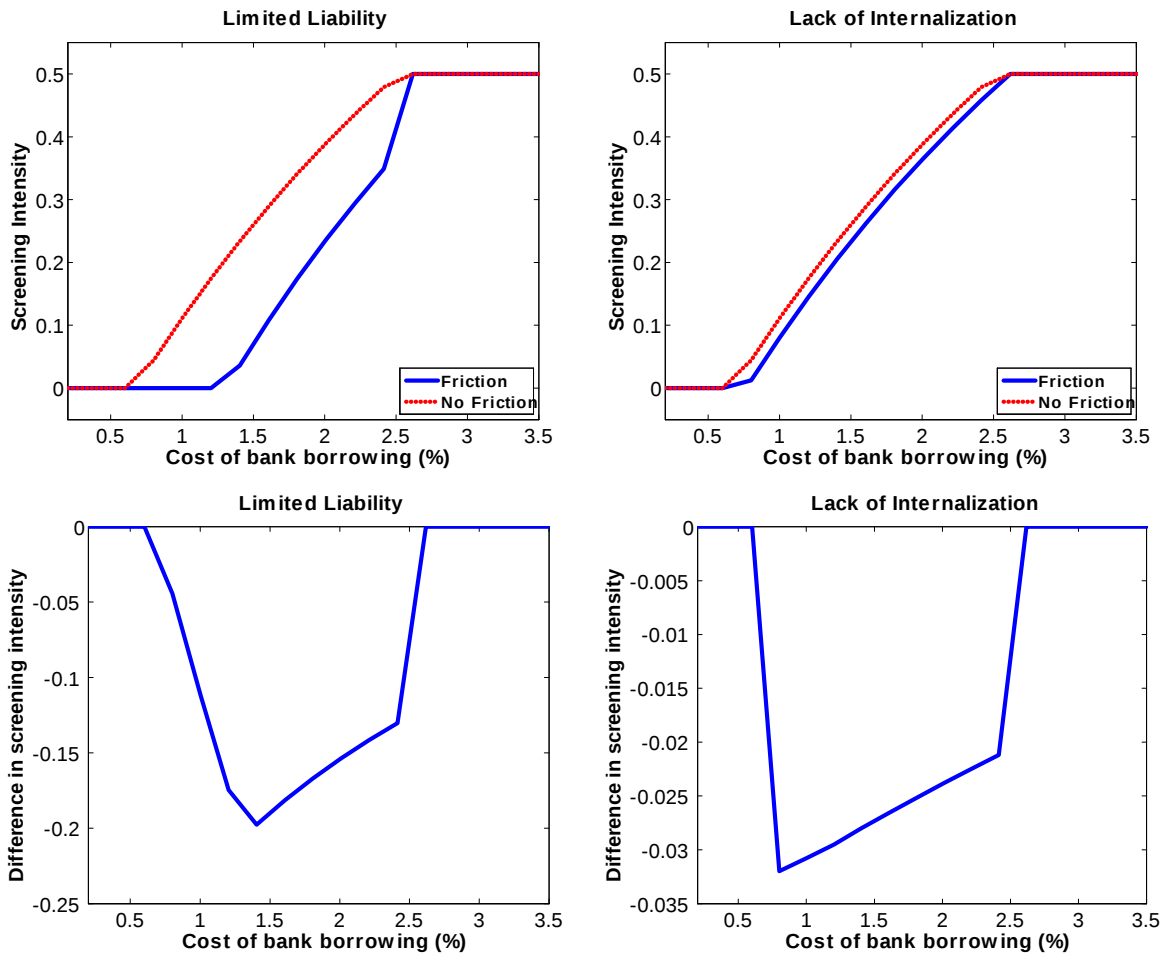


Figure 4: Screening Intensity as a function of the Cost of Bank's Borrowings.
This figure redoes Figure 3 but as a function of the cost of borrowings for the banks.

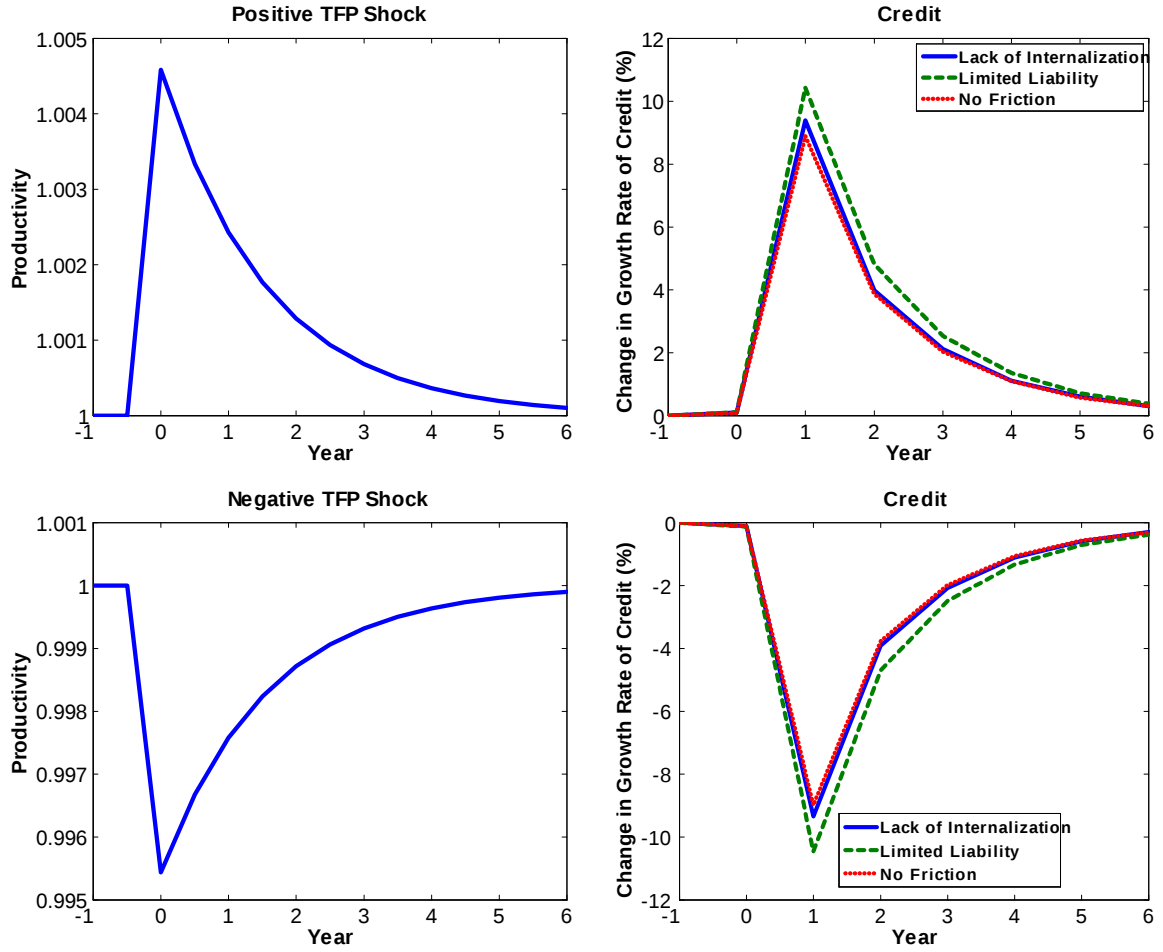


Figure 5: Impulse Responses of Credit to TFP Shocks. The panels on the left plot a positive (upper left panel) and a negative TFP shock (lower left panel). Then the panels on the right plot the associated response in credit for three different cases: 1) Model with only limited liability as friction, 2) model with only lack of internalization as friction, 3) model with no friction.

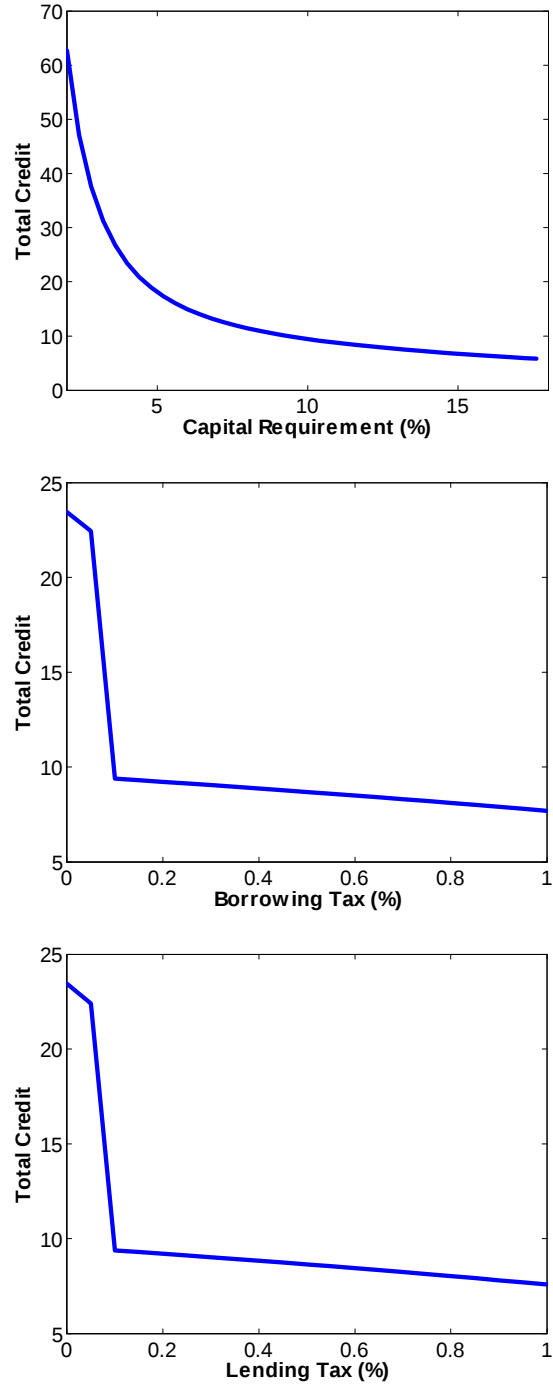


Figure 6: Total Credit and Macroprudential Tools. These figures plot the reaction of total credit to the three macroprudential tools: capital requirements, a tax on bank's borrowings and a tax on bank lending.