Lax Lending Standards and Capital Requirements*

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Abstract

Banks generate excessive low-quality lending if they decide their optimal screening and lending intensities without internalizing that their behavior alters the pool of borrowers faced by other banks. Banks choose to spend too much time finding new customers rather than screening them, leading to an inefficiently high level of credit. This paper conducts a quantitative study of this market failure and then shows how capital requirements remedy it. First, we present a calibrated model whose predictions concerning the quantity and quality of credit are in line with recent U.S. business cycles. Second, we show that the externality amplifies the effects of economic shocks, banks' capital and lending are too volatile. Capital requirements can reduce this excessive volatility if banks' capital is more expensive than external funds. Moreover, optimal capital requirements should be time-varying because the market failure varies with macroeconomic conditions.

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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.[1] The new regulations need to be related to what went wrong, and the list of potential failures always includes lax bank lending standards.[2] In this paper we study a quantitative model with an externality that generates lax lending standards and too much low quality credit, thus "overlending". We show that the model matches well recent U.S. business cycle patterns on the relationship between the quality and quantity of credit. In particular, periods of high loan growth are followed by higher bank losses because credit booms are accompanied by lower lending standards. Then, we illustrate that this overlending amplifies the effects of economic shocks and induces too much volatility in banks' capital. Capital requirements can address this externality if banks' capital is more expensive than external funds, an assumption widely supported by the data (King 2009). Moreover, optimal capital requirements should be time-varying because the externality changes with both bank funding costs and borrowers' productivity.

Our starting point is an inefficiency recently theorized by Hachem (2011). Hachem shows that 1) if individual banks do not internalize that their behavior worsens the quality of the pool of borrowers faced by other lenders, 2) if 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) if lending relationships last several periods, then a competitive equilibrium will generate excessive low quality lending relative to a social planner that internalizes the exter-

[1] Blanchard et al. (2010), and Galati and Moessner (2011) are recent surveys.

[2] See for example Allen and Carletti (2009), Acharya and Richardson (2009), Rajan (2010) and Taylor (2009).

nality. That is, banks screen too little in the competitive equilibrium. Hachem (2011) shows that a tax on the lending activity of individual banks achieves optimality.

Our model modifies Hachem (2011) in several dimensions to perform quantitative analysis and study the role of capital requirements in curbing excessive lending. We keep the three elements that generate the inefficiency and allow for different sizes in the degree to which banks internalize the consequences of their behavior. Different sizes can be viewed as different degrees of banking competition. For example, small banks in very competitive environments will internalize less their impact on the borrower pool than monopolistic banks. Thus, optimal capital requirements should also be conditional in the amount of banking competition.

In the model there is a continuum of firms that are heterogenous in idiosyncratic productivity and are subject to an aggregate productivity shock. Firms' idiosyncratic productivity is private information. Firms have no storage technology and no endowment, so they must borrow from banks in order to produce. Banks give credit using their own capital and external financing subject to a capital requirement constraint. Capital evolves across time depending on the profits or losses of the banking system. External finance is modeled assuming that banks have access to interbank markets to borrow or lend at an exogenous interest rate.[3] We assume this rate to be lower than the cost of using the bank's own capital. This assumption is common in analysis of banking regulation (Allen et al. 2011) because it is an empirical regularity. It can be microfounded by assuming that capital would be the first to take any loan loss (i.e., it is riskier) or debt is tax deductible while equity is not. For simplicity we just assume it and do not model the problem of the bank holders or the interbank markets. Thus, in this dimension our model is a partial equilibrium model.

Banks are endowed with a fixed amount of resources (e.g. time) that they can use to look for borrowers or to screen them.[4] If they 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 firm. However, this productivity is always learned after one period of a credit relationship. If the borrower was bad, the bank might not recover what was lent in the first period. Good customers can be "locked-in" for the next period (except if hit by an exogenous separation shock). Thus, when aggregate credit goes up, in the following period the quality of the pool of

[3] At the aggregate level, the exogenous interest rate assumption corresponds to an economy that is small and open with respect to world capital markets. Boz and Mendoza (2010) provide some empirical justification, citing recent evidence that in the era of financial globalization even the U.S. risk-free rate has been significantly influenced by outside factors. Moreover, post-war U.S. data from the Flow of Funds show that about one half of the surge in net credit since the mid-1980s was financed by the rest of the world.

[4] This assumption is for modelling convenience. It generates an opportunity cost of screening a borrower. An alternative modelling device is to assume that screening is costly and the banks face a budget constraint that limits how many resources they can spend in screening tasks.

available borrowers goes down because only productive firms are retained.

Individual banks do not internalize that by giving credit today they lower the quality of the pool of borrowers tomorrow. This leads them to allocate excessive resources to sales (too little screening) relative to a planner that internalizes the externality.[5] That is, banks follow an "attract now, screen later" behavior and give too much uninformed credit. As a consequence, banks are more exposed to unexpected shocks than the planner would be. After a positive productivity shock, individual banks make more profits than the planner. But they lose more money when a negative shock hits. Thus, banks' capital is too volatile in the competitive equilibrium, which induces excessive volatility in output because loans are partially financed with bank capital.

Capital requirements can achieve the optimal balance of screening and lending because they affect the fraction of each loan financed with outside funding. Since this funding is cheaper than banks' own capital, the lower the capital requirements, the lower the costs for the banks to fund their loans. When these costs go down, so does the quality of the marginal borrower getting credit relative to the social optimum.

The capital requirements that remedy overlending should be time-varying, going up when the size of the overlending externality goes up. This happens when the costs of external funding are low (and banks have strong incentives to borrow), and in the positive side of the business cycle (higher TFP implies that the fraction of profitable borrowers is larger). Also, if more competitive banking systems internalize this externality to a lower degree, they should have higher capital requirement.

The model shows that decreasing lending standards should not be confused with "lax standards". It is optimal for lending standards to be time-varying if macroeconomic conditions are time-varying. Lending intensity should increase when interest rates are low and when GDP or borrower's productivity are growing. The problem is that a competitive banking system does not allocate resources efficiently between screening borrowers and selling product. It allocates too many resources to sales, thus it "overlends". Moreover, this amount of overlending changes with macroeconomic conditions.

In Section 3 we use U.S. data from the last 25 years to document strong comovements between the quantity of credit and the quality of credit (measured by delinquencies and banks' losses). Periods of rapid loan growth are followed by periods of higher delinquency rates. This is a fact already discussed by Greenspan (2001) and it also holds for many other countries (for example Terrones and Mendoza 2008, Elekdag and Wu 2011 or Igan and Pinheiro 2011).

[5] This planner can be a monopolistic bank, or a macroprudential regulator.

We calibrate our model to match several average ratios of the U.S. banking system (return on equity, losses, credit to GDP, 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 credit observed in the data. The model is quite successful. 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.

In simulations of the calibrated model, bank capital and output are 2% more volatile in the competitive equilibrium case relative to the planner. This excessive volatility is due to the overlending externality discussed before. Capital requirements reduce this volatility and must be increasing in the size of the productivity shock and the amount of the externality. For example, given our baseline calibration, when no bank internalizes that it affects the quality of the borrowing pool (the perfect competitive equilibrium), capital requirements would need to increase from 4% to 4.6% (in a calibration to the requirements of Basel I and II for core bank capital).

This paper is connected to several strands of literature:

a) Hachem (2011) provides the theoretical inspiration for our work. We make the following modifications to her model to address a different set of questions: 1) We allow the banks to fund loans with both equity and borrowings, to default, and we introduce capital requirements; 2) We introduce productivity shocks to study business cycles and how expectations interact with overlending; 3) We control for the size of the externality; 4) We abstract from effort choice on the borrower side and assume an exogenous cost of external funds; 5) We convert the infinite horizon problem into a finite horizon problem by assuming that all bank-borrower matches separate at some point, which simplifies the study of the dynamics after shocks.

b) There is an empirical literature studying changes in the lending practices of banks (Asea and Blomberg 1998, Degryse and Ongena 2010, Lown and Morgan 2006, Maddaloni and Peydro 2011 and Wilcox 2009). Several theories have been provided by the literature to explain changes in lending standards (E.g. Berger and Udell 2004, Dell'Aricia and Marquez 2006, Gorton and He 2008, Rajan 1994 or Ruckes 2004). We provide a quantitative model that can account for some of those changes using an unexplored externality.

c) We contribute to the recent literature on quantitative models of banking. Examples include Corbae and D'Erasmo (2010), Covas and Fujita (2010), De Nicolo (2011), De Walque et al. (2010), Gerali et al. (2010), Goodfriend and McCallum (2007), Iacoviello (2010), Martinez-

Miera and Suarez (2011), Meh and Moran (2010), Kollmann et al. (2011), Olivero (2010), Ueda (2012) and Van den Heuvel (2008). Our paper focuses on the trade-off between the quality and the quantity of credit.

d) Most models of capital requirements justify them as a tool to reduce the moral hazard that arises due to deposit insurance (Allen et al. 2011, De Nicolo 2011, or Van den Heuvel 2008).[6] Brunnermeier et al. (2009) advocates for capital requirements to reduce pro-cyclical leverage. Our paper provides a third justification, capital requirements reduce the excessive volatility induced by inefficient lending standards. Moreover, as long as this inefficiency is procyclical, our model provides new arguments for counter-cyclical capital requirements. The standard arguments are based on the procyclicality of bank capital (Kashyap and Stein 2004 provide a survey, Kowalik 2011 discusses the countercyclical capital requirements imposed by Basel III and the Dodd-Frank Financial Reform).

e) Our paper complements the recent literature on macroprudential policy that has focused on pecuniary externalities. This literature has emphasized Pigouvian taxes on borrowings as the main macroprudential tool. Recent examples are Benigno et al. (2010), Bianchi (2011), Bianchi and Mendoza (2011), Gersbach and Rochet (2011), Jeanne and Korinek (2010), Lorenzoni (2008), Perotti and Suarez (2010) or Stein (2011). Pecuniary externalities generate too much volatility in output and borrowing through a different mechanism than our model. Taxes on interbank borrowing would also address our externality.

The structure of the paper is the following: Section 2 presents the model. Section 3 documents some facts about the quality and the quantity of credit. Section 4 calibrates the model and discusses its quantitative properties. Section 5 analyzes the capital requirements that remedy the externality. Section 6 concludes. Appendix I characterizes the value functions of the bank. Appendix II describes the data and the numerical algorithm.

2 Model

The economy is composed of firms and banks that must form lending agreements to finance the production of a single good. Firms' behavior is mechanical: they always look for the maximum available credit. Therefore, all of the interesting action happens on the bank side.

[6] With high levels of leverage, there is an incentive for banks to take on excessive risk. This incentive is reduced if banks have capital at risk.

2.1 Firms

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

$$y(\omega, z_t, L_t) = \theta \omega^{\alpha} z_t L_t \tag{1}$$

where θ and α are parameters, z_t is an aggregate productivity shock with conditional density $f(z_t|z_{t-1})$ and support $[0, \infty)$, and L_t is the size of the loan that the firm receives. Any unfinanced firms will produce zero output.

To ensure that all firms seek the maximum financing, we assume that a fraction $\kappa \geq 0$ of production cannot be seized by the banks for loan repayment. However, because $y(\omega, z_t, L_t)$ is perfectly observable, banks can always recover the remaining fraction, $(1 - \kappa)y(\omega, z_t, L_t)$. This is the interest rate that any bank would charge, thus from the borrower's perspective all banks are alike.

2.2 Banks

At the start of each period there is a continuum of mass one of risk neutral banks each endowed with capital K_t. Banks' objective is to maximize profits over the period, and they make three decisions to do so: 1) how to allocate resources between attracting customers and screening them, 2) whether to keep a borrower when matched, and 3) the size of the loan to extend to a borrower who is kept. These financing decisions are made before the productivity shock (z_t) is realized, thus the bank faces two sources of uncertainty: the idiosyncratic productivity of the borrower and aggregate productivity.

Each period has four stages, illustrated in Figure 1, and banks default along them. For simplicity, we assume that the capital of those banks not defaulting remains fixed at K_t until the end of the period.

Insert Figure 1 about here

For expositional purposes let's denote the stages 1a, 1b, 2a and 2b:

1) In stage 1a, the bank has to allocate one unit of resources between attracting customers or screening them. We denote by π_{1t} the fraction of resources spent on matching with borrowers, and by $(1 - \pi_{1t})$ the fraction spent on screening. Additionally, π_{1t} will be

the probability of matching, and $(1-\pi_{1t})$ the probability of successfully discovering a borrower's type. Thus, there is a tradeoff between screening and lending. Banks may only match with one borrower at a time. 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 $(1-\pi_{1t})$.

2) In stage 1b, banks that remained unmatched in stage 1a invest their capital in the interbank market at rate i_b. Banks that successfully matched with a borrower must decide whether to extend credit, and this decision depends on whether the bank is informed or uninformed. The informed bank will lend to a borrower if her expected return allows her to repay the bank's borrowings plus a minimum return on equity, i_k. Hence, the pivotal borrower $\overline{\omega}_1$ is the type ω satisfying

$$\int_0^\infty (1-\kappa)y(\bar{\omega}_1, z_1, L_t)f(z_1|z_{-1})dz_1 = (1+i_b)B_t + (1+i_k)K_t \tag{2}$$

Informed banks will give credit to those firms with better expected productivity than that of the pivotal borrower, so the decision rule is given by:

$$A_1(\omega, z_{-1}) = \begin{cases} 0 & \text{if} \quad \omega < \overline{\omega}_1 \\ 1 & \text{if} \quad \omega \geq \overline{\omega}_1 \end{cases} \tag{3}$$

Uninformed banks do not know their borrower's type, so they will only give credit if the borrower they expect to meet has an expected return that is high enough to break even:

$$A_1^\omega(z_{-1}) = \begin{cases} 0 & \text{if} \quad \int_0^1\int_0^\infty (1-\kappa)y(\omega, z_1, L_t)f(z_1|z_{-1})\psi_1(\omega)dz_1 d\omega < (1+i_b)B_t + (1+i_k)K_t \\ 1 & \text{if} \quad \int_0^1\int_0^\infty (1-\kappa)y(\omega, z_1, L_t)f(z_1|z_{-1})\psi_1(\omega)dz_1 d\omega \geqslant (1+i_b)B_t + (1+i_k)K_t \end{cases} \tag{4}$$

where $\psi_1(\omega)$ is the density function of available borrowers of type ω in stage 1a (we define it in the next section). Those banks that choose not to give credit (i.e., either $A_1(\omega, z_{-1}) = 0$ or $A_1^\omega(z_{-1}) = 0$) invest their capital in the interbank market at rate i_b.

To finance the loan, banks can use their own capital or they can borrow in interbank markets at rate i_b. For banks it is optimal either to lend nothing or the maximum amount

(L). This maximum amount depends on the bank's capital and interbank borrowings, but subject to a capital requirement, $\gamma \geq 0$, such that

$$L_t = B_t + K_t \tag{5}$$

$$K_t \geq \gamma L_t \tag{6}$$

We will solve for an equilibrium where the cost of outside funding (i_b) is smaller than the cost of bank equity (i_k). Both are exogenous and we calibrate them to averages of past periods. Setting $i_b < i_k$ implies that the capital requirement binds, thus period t loans and borrowings are

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

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

Combining equations (7) and (8) with the decision rules discussed above, we have that the bank's choice of whether or not to extend credit does not depend on the amount of bank capital. However, the capital requirement does play a role because the ratio of borrowings to capital is affected by γ and inside financing is more expensive.

3) At the start of stage 2a the productivity shock is realized and all banks discover their borrower's type. Banks who gave credit either made enough profits to repay outside funding plus the minimum return to their own funds, i_k, or not. To track which banks make profits, we use the following indicator function that takes the value one when a bank is profitable

$$\Omega_1(\omega, z_1) = \begin{cases} 0 & \text{if} \quad R(\omega, z_1)L_t < (1+i_b)B_t + (1+i_k)K_t \\ 1 & \text{if} \quad R(\omega, z_1)L_t \geq (1+i_b)B_t + (1+i_k)K_t \end{cases} \tag{9}$$

where R_t is the realized return on a borrower of type ω after the productivity shock of stage 1b.

Profitable banks can keep their borrowers into stage 2a if not hit by an exogenous separation shock, μ. Unprofitable banks disappear and their losses reduce the aggregate stock of capital.[7] Banks who did not default and are without a customer from before decide π_{2t}, the fraction of resources spent on matching with borrowers, given their beliefs on the

[7] Thus at the start of stage 2a the mass of banks is smaller than one, and aggregate capital available for lending is smaller than K_t.

evolution of the borrower distribution.

4) In stage 2b banks who are matched with a borrower must decide whether to extend credit to the borrower (as in stage 1b), but now some banks have defaulted and the quality of the pool of available borrowers 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. New banks enter so that we again have mass one of banks. To avoid keeping track of each individual bank's capital we assume that profits are integrated into the aggregate capital stock and that this is equally distributed among the continuum of banks.

Each bank's objective is to maximize profits (P_t, defined in Subsection 2.4) over the period. Aggregate bank capital evolves according to

$$K_{t+1} = K_t + P_t \tag{10}$$

To simplify notation, 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 1a or 1b of period t we will just write π_1. For productivity we will denote by z_{-1} the second shock of period $t-1$, by z_1 the first shock of period t and by z_2 the second shock of period 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.

2.3 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. If banks take Π as an exogenous constant, for example because they are small or do not recognize that their actions affect aggregate lending intensity, they do not internalize the effect of their choice of π on Π, and the externality is at its maximum. However, if banks correctly internalize that their choice of lending intensity alters the distribution of borrowers, there is no externality. Following Hachem (2011) we call these cases the competitive equilibrium and the planner equilibrium.

To allow for externalities of different sizes, we assume that banks form their expectations about Π based upon a combination of their own lending intensity and an exogenous belief (Π^g). We discipline this belief by solving for equilibria with individual choices of lending intensity

equal to aggregate lending intensity and bank beliefs

$$\Pi_i = \zeta\pi_i + (1-\zeta)\Pi_i^g \qquad i = 1, 2 \tag{11}$$

$$\Pi_i = \pi_i = \Pi_i^g \quad \forall i \tag{12}$$

The parameter $\zeta \in [0, 1]$ captures the size of the externality and can be interpreted as the amount of banking competition. For $\zeta < 1$, there is some externality. The case where $\zeta = 0$ is the competitive equilibrium. As ζ increases, the individual bank realizes she affects aggregate lending intensity more and more. The case where $\zeta = 1$ is the planner's problem.

Banks have two different borrower distributions to consider in stage 1a of each period:

1) The distribution of matched borrowers with informed financing, $\lambda(\omega)$. Because all banks and borrowers begin stage 1a unmatched, the probability of a borrower of type ω receiving informed financing in stage 1a is

$$\lambda_1(\omega) = \Pi_1(1-\Pi_1)A_1(\omega, z_{-1}) \tag{13}$$

where $\Pi_1(1-\Pi_1)$ is the probability of a match in stage 1a with an informed bank. $A_1(\omega, z_{-1})$ is an indicator function with value one if a borrower of type ω receives financing from the informed bank. The decision to give informed credit depends on the borrower type, ω, and on expected productivity, z_1, whose expectation is a function of past productivity, z_{-1}.

2) The distribution of matched borrowers with uninformed financing, $\phi(\omega)$. In stage 1a the probability of a borrower of type ω being matched with an uninformed bank giving credit is

$$\phi_1(\omega) = \Pi_1^2 A_1^\omega(z_{-1}) \tag{14}$$

where Π_1^2 is the probability of a first period match with an uninformed bank. $A_1^\omega(z_{-1})$ is an indicator function with value one if the uninformed bank gave credit. Since the bank does not know the borrower's type, she needs to form an expectation.

Expectations about available borrowers are made using banks' beliefs about the pool of unmatched borrowers at the start of stage 1, $\psi_1(\omega)$. In the first stage, all borrowers start unmatched, thus the banks' beliefs about the density of type ω being in the pool of available borrowers is the initial uniform distribution on the unit interval

$$\psi_1(\omega) = 1 \tag{15}$$

In stage 2a, banks update their beliefs because they know that the pool of available borrowers has changed. A borrower is in this pool if she did not match in stage 1a or did not receive credit in stage 1b, $\lambda_1(\omega) = 0 = \phi_1(\omega)$, if she was found unprofitable at the start of stage 2a $(\Omega_1(\omega, z_1) = 0)$, if she was profitable but hit by separation shock with probability μ, or if she was profitable but she is not expected to be profitable in the second stage $(A_2(\omega, z_1) = 0)$.[8] Thus, the probability of meeting type ω in the pool of available borrowers in the second stage is

$$\psi_2(\omega) = \frac{1 - A_2(\omega, z_1)\Omega_1(\omega, z_1)(1-\mu)(\lambda_1(\omega) + \phi_1(\omega))}{\int_0^1 [1 - A_2(\omega, z_1)\Omega_1(\omega, z_1)(1-\mu)(\lambda_1(\omega) + \phi_1(\omega))]\, d\omega} \tag{16}$$

The size of the pool of unmatched banks in stage 2a, η_2, is the total mass of banks, minus the fraction of banks who matched and made negative profits, minus the fraction of banks who remain matched

$$\eta_2 = 1 - \int_0^1 [(1 - \Omega_1(\omega, z_1)) + A_2(\omega, z_1)\Omega_1(\omega, z_1)(1-\mu)]\,(\lambda_1(\omega) + \phi_1(\omega))d\omega \tag{17}$$

The amount of available banks affects the number of matches formed in the second stage. For example, the amount of new informed matches at the end of stage 2a is $\eta_2\Pi_2(1 - \Pi_2)$.

In stage 2b:

1) The distribution of matched borrowers with informed financing is

$$\lambda_2(\omega) = A_2(\omega, z_1)\Omega_1(\omega, z_1)(1-\mu)(\lambda_1(\omega) + \phi_1(\omega)) + A_2(\omega, z_1)\eta_2\Pi_2(1 - \Pi_2)\psi_2(\omega) \tag{18}$$

   where the first term is the fraction of profitable borrowers financed last period who were not hit by the separation shock and were rolled-over. The second term 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 and was given credit $(A_2(\omega, z_1) = 1)$.

2) The distribution of matched borrowers with uninformed financing is

$$\phi_2(\omega) = \psi_2(\omega)\eta_2\Pi_2^2 A_2^{\omega}(z_1) \tag{19}$$

[8] Borrowers expected to be unprofitable in stage 2b are with probability one in the pool of available borrowers at stage 2a, because all banks discover their stage 1 borrower's type at the beginning of stage 2a. Thus, no bank keeps them, $A_2(\omega, z_1) = 0$.

The first term represents the fraction of available borrowers, and this is multiplied by the probability that these unmatched borrowers receive uninformed financing.

2.4 Profits of the Banking Sector

The aggregate profits of period t are the profits of the informed banks, plus the profits of the uninformed banks, plus the profits of the unmatched lenders across both stages. Using the notation from the previous section, we can account for how many banks are in each situation:

$$P_t = \int_0^1 \left\{ \begin{array}{c} [R(\omega, z_1)L_t - (1+i_b)B_t - K_t]\,(\lambda_1(\omega) + \phi_1(\omega)) + \\ +i_b K_t\,(1 - \lambda_1(\omega) - \phi_1(\omega)) + \\ +[R(\omega, z_2)L_t - (1+i_b)B_t - K_t]\,(\lambda_2(\omega) + \phi_2(\omega)) + \\ +i_b K_t[\eta_2 - \phi_2(\omega) - [\lambda_2(\omega) - A_2(\omega, z_1)\Omega_1(\omega, z_1)(1-\mu)\,(\lambda_1(\omega) + \phi_1(\omega))]] \end{array} \right\} d\omega \tag{20}$$

where the last term accounts for those banks unmatched at the start of the second stage (η_2) that do not match (ϕ_2 are the uninformed matches, and $\lambda_2(\omega) - A_2(\omega, z_1)\Omega_1(\omega, z_1)(1 - \mu)\,(\lambda_1(\omega) + \phi_1(\omega))$ are the new informed matches from equation 18).

3 Some Facts about the Quality and Quantity of Credit

In this section, we document business cycle facts about the quality and quantity of bank credit in the U.S. Our 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.[9] The sources for the data are listed in Appendix II.

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 (the charge-off rate is the value of loans charged against loss reserves). Both credit quality variables are strongly positively correlated and lag the quantity of credit cycle.

Insert Figure 2 about here

Panel B plots the cyclical components of the quantity and quality of business credit against

[9] We used an H-P filter with parameter set to 100 to detrend the series.

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.[10] 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 Figure 2.

Insert Table 1 about here

4 Results and Quantitative Analysis

The model does not have analytical solutions. Thus we solve it numerically after calibrating it to match some average ratios of the U.S. banking system.[11] To illustrate how the model works we discuss first the optimal choices of lending intensity. Then we simulate business cycles in the model and show its ability to replicate the facts discussed in Section 4. Finally we show the key result of the paper: the overlending externality generates excessive volatility in output, credit and capital.

4.1 Calibration

Table 2 summarizes our parameterization. We calibrate one period in the model to be one year and use U.S. annual data from 1987-2010. Our calibration targets the model when productivity is at its long run mean, i.e. the no shock case. Also, we calibrate to the perfectly competitive case ($\zeta = 0$, i.e., no internalization at all of the externality).

Insert Table 2 about here

For the firm's technology, we set θ to 10.7 to target a ratio of the stock of business loans by commercial banks to GDP of 9.71%, which is the average we see in FRED data over our

[10] An interesting pattern to notice is that in the first two business cycles of the sample period, the peaks and troughs of production and the quantity of credit occur in roughly the same time period. In the most recent cycle, however, production peaks before the quantity of credit.

[11] In equilibrium, for exogenous productivity and cost of funds, firms and banks optimize. The problem of a firm is trivial: always look for credit. Bankers maximize profits by choosing π_i, $A_i(\omega, z_{i-1})$, $A_i^{\omega}(z_{i-1})$, L_i and R_i $\forall i$ subject to borrower distributions and beliefs (11) – (19), capital requirements (6) and the symmetry condition (12) .

sample period.[12] The curvature parameter α is set so that the ratio of losses to loans matches the 0.91% ratio reported in FRED's series of losses on commercial loans.

We set the average interbank borrowing rate i_b to 4%, matching the average 12-month U.S. interbank rate since 1992. We assume that banks target a minimum return to capital, i_k, of 7%. This is among the lower estimates of the cost of equity across 99 sectors estimated by Damodaran (2011). To calibrate the fraction of unseizable profits (κ), we target an average return on equity of 11.9%, which is our estimate of the average return on bank equity during 1987-2010 using the FRED database. Exogenous separation probability μ is set to 40% so that in the model the percentage of the loan portfolio in the second stage that is carried over from the first one matches the carry-over ratio of 71% reported by Bharath et al. (2009).

Initial capital is normalized to 1, and we assume a capital requirement of 4%, which was the Tier 1 capital requirement under Basel I. Basel I was the regulation applied over most of our sample period.

Following Bianchi and Mendoza (2010), we assume a log-normal AR(1) process for productivity:

$$\log z_t = \rho_z \log z_{t-1} + \varepsilon_{z,t} \tag{21}$$

$$\varepsilon_{z,t} \sim N\left[0, \sigma_z^2\right] \tag{22}$$

and we calibrate the persistence, ρ_z, and variance of the shock process, σ_z^2, to a semestral frequency since we have two shocks per period.

4.2 Comparative Statics in the Deterministic Model

To show the intuition behind the model, Figure 3 reports two comparative statics exercises. Panel A shows the optimal lending intensity chosen by banks when $\zeta = 0$ and $\zeta = 1$ as the interbank interest rate changes.

Insert Figure 3 about here

The optimal lending intensity for both individual banks and the planner decreases as the interest rate rises. The banks face a tradeoff between allocating resources to screening or to matching with borrowers. When the cost of funding is higher it is more risky to give credit

[12] We focus on business loans because most of them are not collateralized.

without knowing the borrower's type. Thus higher cost of funding encourages banks to spend more time screening their borrowers to ensure profitability. This result is key to understand the role of capital requirements that we discuss in the next section.

In Panel A, when the interest rate is very low, the pool of borrowers is highly profitable and we see that banks choose to spend all of their resources on matching. However, when the interest rate is high enough, banks want to lend only to those borrowers they know are profitable and try to maximize their chances of making an informed match by choosing $\pi = 1/2$.

In between these two extremes of Panel A, the optimal lending intensity chosen in the competitive equilibrium case is always higher than the one chosen by the planner. This result demonstrates that when the planner takes into account the effect of lending intensity on the borrower distributions, the optimal response is to decrease lending intensity today in favor of enhanced profitability tomorrow.

Panel C plots the size of the difference in lending intensities as the interbank rate changes. For the most part, the size of the externality decreases in the cost of bank funding. Thus, the overlending externality increases in periods where the cost of funds is low.

Panels B and D redo Panels A and C but for different levels of aggregate productivity (i.e., changes in the average quality of the borrower pool). As the quality of the borrower pool worsens, all banks find it optimal to decrease lending intensity in favor of more screening. And, similar to what we see in Panel A, the planner's choice of lending intensity is below that of the competitive equilibrium except at the extremes, where all banks behave in the same way. Panel D shows that the size of the externality is mostly increasing as aggregate productivity rises. Thus, the overlending externality is pro-cyclical.

An important message from Figure 3 is that reducing the lending standards should not be confused with "lax standards" because optimal lending standards should change with productivity. The problem is that a competitive banking system does not allocate resources efficiently between screening borrowers and selling credit. It allocates too many resources to sales, thus it "overlends".

4.3 Volatilities and Correlations

In this and the following subsection, we discuss the results of simulating the model in response to productivity shocks.[13] Table 3 reports the correlation of the quantity of credit

[13] We explain our numerical procedure in the Appendix II.

with the quality of credit from the model (for the case $\zeta = 0$). We find that the model generates quality of credit which is 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 competitive equilibrium of 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 and the choices of lending intensities and pivotal borrowers. The relative volatilities from the model also resemble the volatilities relative to industrial production.

Insert Table 4 about here

4.4 Amplification Effects

A core result of the paper is that the presence of the overlending externality generates amplification effects in response to economic shocks. If $\zeta < 1$, banks do not internalize all the effects of their actions and are more exposed to uninformed credit than a planner ($\zeta = 1$) would be. This 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 bank's earnings when $\zeta < 1$. Given that banks' earnings determine the amount of capital available for lending in the future, and that our model economy requires credit in order to produce, all variables of an economy with $\zeta < 1$ are more volatile than a planner would be. Table 5 shows this result. All variables are around 2% more volatile in the competitive equilibrium than for the planner.

Insert Table 5 about here

5 Capital Requirements

In this section we discuss why capital requirements can reduce the excessive volatility discussed in Subsection 4.4. The intuition comes from Figure 3. An increase in capital requirements affects the economy by reducing the size of loans (equation 7) and by increasing the cost for the bank of funding the loan, as banks need to use more of their own capital which is more expensive $(i_b < i_k)$. Thus, banks facing higher capital requirements are more conservative in giving credit and prefer to screen their borrowers more. Panel A of Figure 4 confirms these results. It plots the difference between the lending intensities of the planner and the competitive equilibrium in stage one as a function of the capital requirements in the economy with no shocks. The overlending externality decreases as capital requirements increase.

Insert Figure 4 about here

Capital requirements should be function of the factors that affect the externality. Thus, if these factors are time-varying the requirements also should vary. Panel B of Figure 4 illustrates this idea. It plots, for the simulated business cycles of Table 5, the addition to the benchmark capital requirement of 4% needed so that banks with $\zeta < 1$ choose the same allocation of resources between lending and screening as a planner facing a 4% requirement. The results are displayed as a function of firms' TFP (quality of the borrower pool) for different levels of internalization of the externality (different values of ζ in equation 11). The lower is ζ (which can be associated with higher banking competition), the higher the requirements must be. For example, with no productivity shocks when $\zeta = 0$ the capital requirements should be increased to 4.6% for the competitive equilibrium to behave as a planner that just faces capital requirements of 4%.

Also, Figure 4 Panel B illustrates that capital requirements should be increasing in productivity.[14] Regulators should "lean against the wind" and increase capital requirements in good times because when the fraction of profitable borrowers is larger banks internalize less their effects on the borrower's pool.

[14] Capital requirements would be decreasing in the banks' cost of funds if we allowed them to change, for example by adding interest rate shocks to the model.

6 Conclusions

We have studied a market failure proposed by Hachem (2011) that leads banks to allocate too little resources to screening borrowers and too many to giving credit. The externality arises because individual banks do not internalize the effect of their lending decisions on the pool of borrowers faced by other banks.

Our quantitative model displays patterns very similar to the empirical regularities of the quantity and quality of bank credit in the U.S. that we documented in Section 3. For example, periods of high credit volume are followed by increases in loan delinquencies because banks gave too much low-quality credit. The model also matches well the volatilities of banking variables.

We showed that this overlending externality generates excessive volatility in the business cycles of banking variables and aggregate output. In our calibrated model, the economy would be 2% less volatile if banks correctly internalized the externality.

Capital requirements limit bank borrowing and alter the cost of funds. They help to minimize overlending by mitigating individual banks' incentives to take risks. This leads to a higher level of borrower screening. Moreover, capital requirements should be time-varying because the overlending externality is time-varying.

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

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7 Appendix I: Bank's Value Functions

A bank can be in 3 different situations: 1) unmatched with a borrower (we denote the value function by U), 2) matched with a borrower knowing the borrower type (value function J), or 3) matched with a borrower without knowing the borrower type (value function N).

7.1 Unmatched Bank

If the bank is unmatched, he chooses π_1 and π_2 to maximize expected profits. The first period value function is

$$U_1(\psi_1, K_t, z_{-1}) = \max_{\pi_1} \pi_1^2 N_1(\psi_1, K_t, z_{-1}) + \pi_1(1-\pi_1)\int_0^1 J_1(\omega, K_t, z_{-1})\psi_1(\omega)d\omega + \\ + (1-\pi_1)\left[i_b K_t + E_1[U_2(\psi_2, K_t, z_1)]\right] \tag{23}$$

with

$$E_1[U_2(\psi_2, K_t, z_1)] = \int_0^\infty U_2(\psi_2, K_t, z_1) f(z_1|z_{-1})dz_1 \tag{24}$$

The first term of $U_1(.)$ is the probability of forming an uninformed match times the value of such a match, the second term is the probability of forming an informed match times the value of such a match, and the third term is the probability of remaining unmatched times the value of being unmatched (the return from lending on the interbank market plus expected value of being unmatched in the second period).

Similarly, in the second period the value function is

$$U_2(\psi_2, K_t, z_1) = \max_{\pi_2} \pi_2^2 N_2(\psi_2, K_t, z_1) + \\ + \pi_2(1-\pi_2)\int_0^1 J_2(\omega, K_t, z_1)\psi_2(\omega)d\omega + \\ + (1-\pi_2)i_b K_t \tag{25}$$

7.2 Matched Bank Knowing Borrower's Type

In stage 1b, if the bank is matched and knows her borrower's type, she chooses whether to keep her borrower or not. The financing decision is made before the productivity shock z_1 is known. The value function of a matched informed bank in the first period is

$$J_1(\omega, K_t, z_{-1}) = \max_{A_1=\{0,1\}} (1 - A_1(\omega, z_{-1})) \left[i_b K_t + E_1[U_2(\psi_2, K_t, z_1)] \right] +$$
$$+ A_1(\omega, z_{-1}) \left\{ \begin{array}{c} \int_0^\infty (1-\kappa) y(\omega, z_1, L_t) f(z_1|z_{-1}) dz_1 - (1+i_b)B_t - (1+i_k)K_t + \\ +\mu E_1[U_2(\psi_2, K_t, z_1)] + \\ +(1-\mu) E_1[J_2(\omega, K_t, z_1)] \end{array} \right\} \tag{26}$$

where the expectations $E_1[U_2(.)]$ and $E_1[J_2(.)]$ are taken over future productivity shocks as in (24).

The value of an informed match in the second period is

$$J_2(\omega, K_t, z_1) = \max_{A_2=\{0,1\}} (1 - A_2(\omega, z_1)) i_b K_t + \tag{27}$$
$$+ A_2(\omega, z_1) \left\{ \begin{array}{c} \int_0^\infty (1-\kappa) y(\omega, z_2, L_t) f(z_2|z_1) dz_2 + \\ -(1+i_b)B_t - (1+i_k)K_t \end{array} \right\} \tag{28}$$

7.3 Matched Bank Who Does Not Know Borrower's Type

The stage 1a value function of a matched bank that does not know her borrower type is

$$N_1(\psi_1, K^t, z_{-1}) = \max_{A_1^\omega=\{0,1\}} (1 - A_1^\omega(z_{-1}))\left[i_b K_t + E_1[U_2(\psi_2, K_t, z_1)]\right] +$$

$$+A_1^\omega(z_{-1})\left\{\begin{array}{c} \int_0^1\int_0^\infty (1-\kappa)y(\omega, z_1, L_t)f(z_1|z_{-1})\psi_1(\omega)dz_1 d\omega - (1+i_b)B_t - (1+i_k)K_t + \\ \\ +\left[\int_0^1 A_1(\omega, z_{-1})\psi_1(\omega)d\omega\right]\left[\begin{array}{c} \mu E_1[U_2(\psi_2, K_t, z_1)] \\ +(1-\mu)\int_0^1 E_1[J_2(\omega, K_t, z_1)]\psi_1(\omega)d\omega \end{array}\right] \end{array}\right\} \tag{29}$$

where the last product of terms accounts for fact that uninformed banks lending to profitable borrowers, $\left[\int_0^1 A_1(\omega, z_{-1})\psi_1(\omega)d\omega\right]$, can either become unmatched, $\mu E_1[U_2(\psi_2, K_t, z_1)]$, or keep the borrower in the second period.

The value of an uninformed match in the second period is

$$\begin{aligned} N_2(\psi_2, K_t, z_1) = & \max_{A_2=\{0,1\}} (1 - A_2^\omega(z_1)) i_b K_t + \\ & + A_2^\omega(z_1)\left\{\begin{array}{c} \int_0^1\int_0^\infty (1-\kappa)y(\omega, z_2, L_t)f(z_2|z_1)\psi_2(\omega)dz_2 d\omega + \\ -(1+i_b)B_t - (1+i_k)K_t \end{array}\right\} \end{aligned} \tag{30}$$

8 Appendix II: Data and Computation

8.1 Data

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 ($BUSLOANS$), 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 ($CORBLACBS$)

Data Definitions: ROE is net income/equity. Business credit/GDP is total business loans by commercial banks over GDP. Loans carried over in the model is the amount of loans carried over from stage 1b as a percentage of total loans in the second stage. The business loan charge-off rate is the value of loans charged against loss reserves. In the model, this is the value of loan losses over total loans. Delinquencies in the model are the fraction of loans making losses divided by the total amount of loans. The data used here for comparison are 90-day delinquency rates on business loans.

8.2 Computation Procedure

8.2.1 Solution Algorithm

Since this is a 2-stage model, 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, depending on the degree to which they internalize that π_1 affects Π_1 (equation 11) . The solution algorithm is as follows:

1. Discretize the range of π. We use 100,000 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 21), compute expectations about future productivity, z_1 and z_2.
3. For a conjectured guess of Π_1, compute the second stage beliefs about the available borrower pool (equation 16).

4. Solve for the second stage informed and uninformed lending cutoffs ($\overline{\omega}_2$ and A_2^{ω}) as well as the optimal π_2. Call this value π_2^*.

5. Solve for the first stage informed and uninformed lending cutoffs ($\overline{\omega}_1$ and A_1^{ω}). Then solve for the optimal first stage lending intensity π_1, which we denote by π_1^*. It maximizes the first stage objective function (equation 23) taking into account that second stage beliefs ($\psi_2(\omega)$) are affected by π_1 through the degree of internalization of the externality (equation 11).

6. If the conjectured guess of Π_1 in step 3 does not match π_1^*, update the guess in step 3. Repeat steps 3 through 7 until convergence according to the stopping criterion $\mid \Pi_1 - \pi_1^* \mid < 0.0001$.

8.2.2 Simulations

We simulate the model in response to productivity shocks by computing 800 different time series that are 100 periods long. Periods are connected via the productivity process (equation 21) and the transition equation for capital (equation 10). 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 the initial capital, K_0, of each time series to 1, without loss of generality.

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[15] to the log of each variable, and then use these detrended data to compute volatilities and correlations. We then take the average volatilities and correlations of all of our variables of interest over the 800 time series and report them in Tables 3-5.

[15] Our model is calibrated to an annual frequency, so we choose a parameter value of 100 for the HP-filter. This choice coincides with the filter we used to compute the data moments.

Tables

Table 1: Comovement of Quality & Quantity of Credit

	Cross Correlation of									
	Total Loans at time t with					Business Loans at time t with				
Variable x	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 (more details 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 stock business loans to GDP of 9.71% as in FRED, in model: 9.79% when no shock
α	0.07	Ratio of business losses to loans of 0.91% as in FRED, in model: 1.03% if no shocks
i_k	0.07	Minimum capital return of at least 7% per year (Damodaran 2011)
i_b	0.04	Average U.S. 12-month interbank borrowing rate
μ	0.4	Loans carried over of 71% as in Bharath et al. (2009), in model: 76.8% when no shocks
κ	0.895	Average return on equity of 11.94% as in FRED, in model: 16.5% when 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) target for U.S. productivity process, modified for 1/2 year
σ_z	0.009	Bianchi and Mendoza (2011) target for U.S. productivity process, modified for 1/2 year

Table 3: Comovements in the Model (Case $\zeta = 0$)

	Cross Correlation of Loans at time t with				
Variable x	x(t-2)	x(t-1)	x(t)	x(t+1)	x(t+2)
Quality of Credit:					
Delinquency Rate	-0.09	-0.12	-0.13	0.84	0.18
Charge-off Rate	-0.06	-0.01	0.11	0.88	0.12
Model simulated as discussed in Appendix II					

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:			
Delinquency Total Loans	0.39	0.23	0.14
Charge-off Rate on Total Loans	0.16	0.1	0.01

Note: Annual data for years 1987-2010 (more details in the Appendix). Data detrended with the HP filter with smoothing parameter 100. Model simulated as discussed in footnote 8.

Table 5: Excessive Volatility over the Business Cycle

	Std. Dev.		
	Competitive Eq'm	Planner	Ratio Comp. Eq'm to Planner
Output	0.503	0.494	0.983
Bank Profitability			
Return on Equity	0.193	0.191	0.992
Quantity of Credit			
Total Loans	0.510	0.501	0.982
Quality of Credit			
Delinquency Rate	0.071	0.070	0.986
Charge-off Rate	0.005	0.005	0.983

Model simulated as discussed in Appendix II

Figures

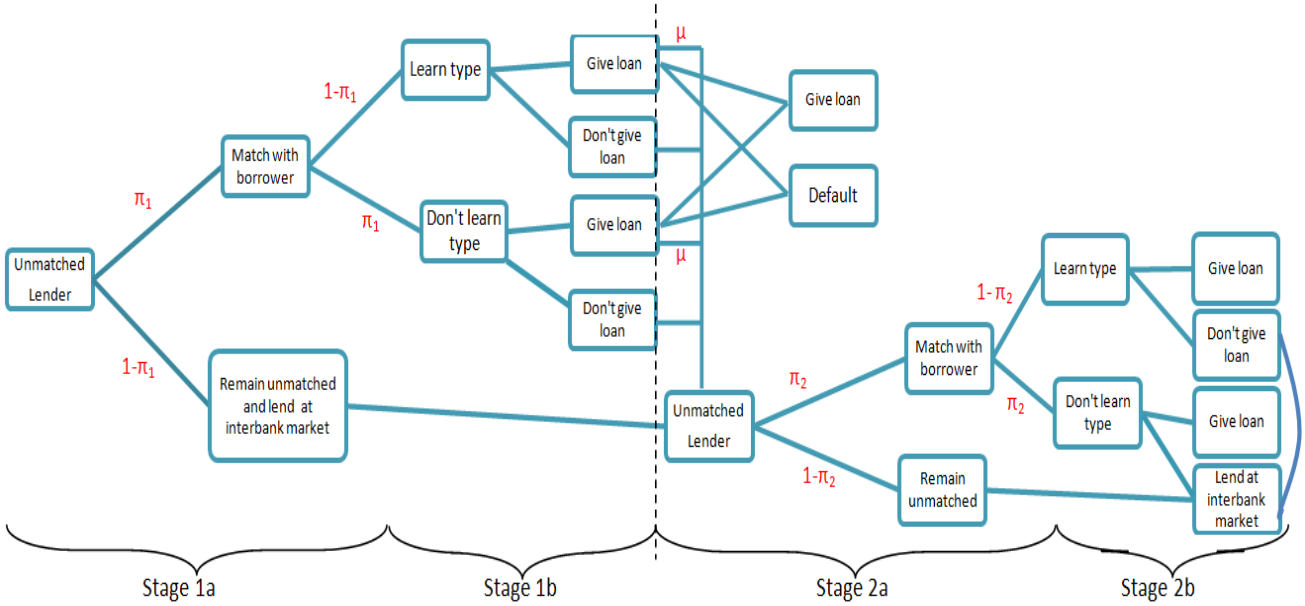

Figure 1: Summary of Bank's Problem

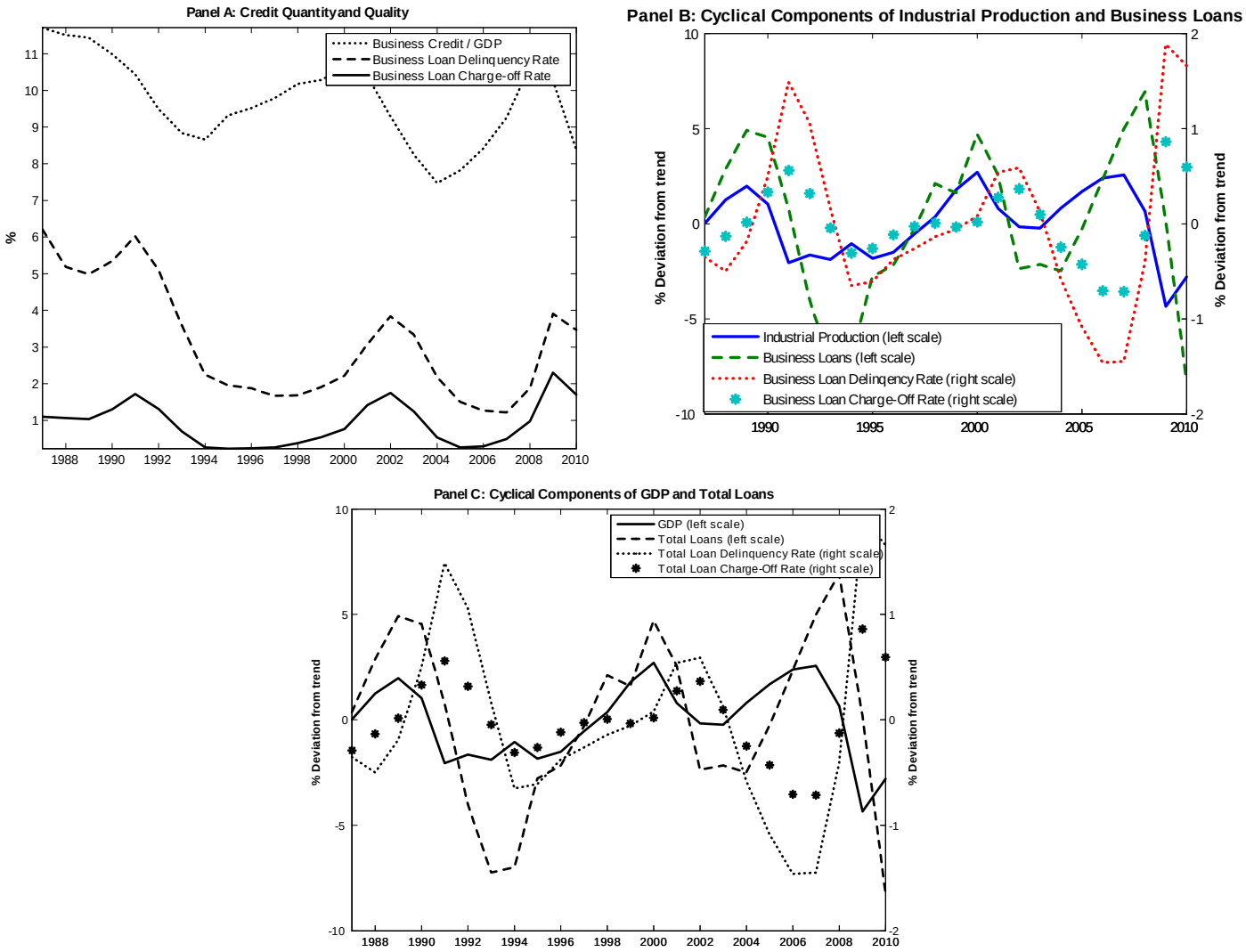

Figure 2: Facts about the Quantity and Quality of Credit. Panel A plots the business credit to GDP ratio against the delinquency rate and the charge-off rates on commercial and industrial loans. Panel B plots the cyclical component of industrial production, the quantity of business credit, the delinquency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

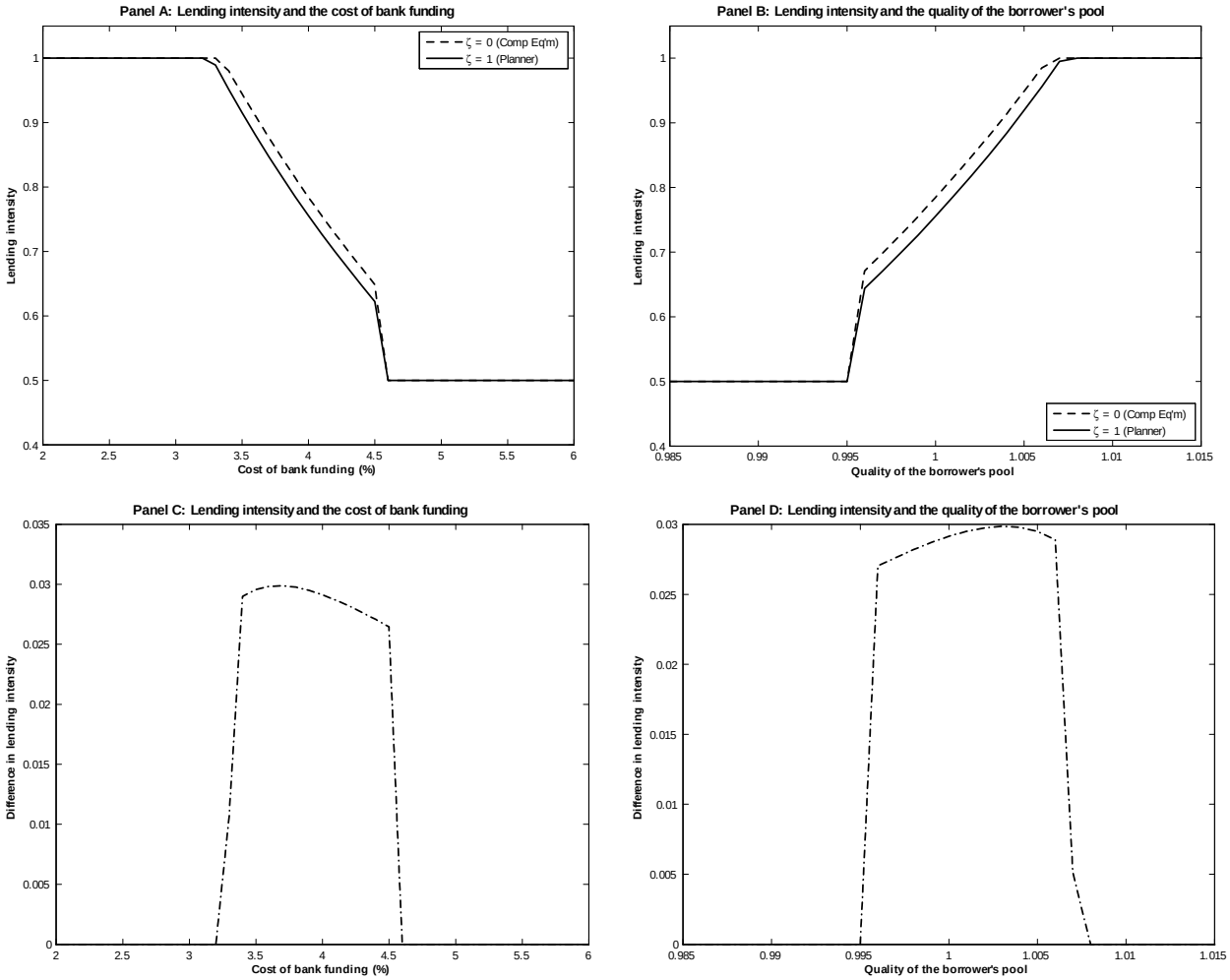

Figure 3: Lending Intensity. Panel A plots the lending intensity at stage 1a for the Planner and Competitive Equilibrium as a function of the cost of bank funds. Panel C plots their differences. Panel B plots the same lending intensities as a function of firm's TFP (quality of the borrower pool). Panel D plots their differences.

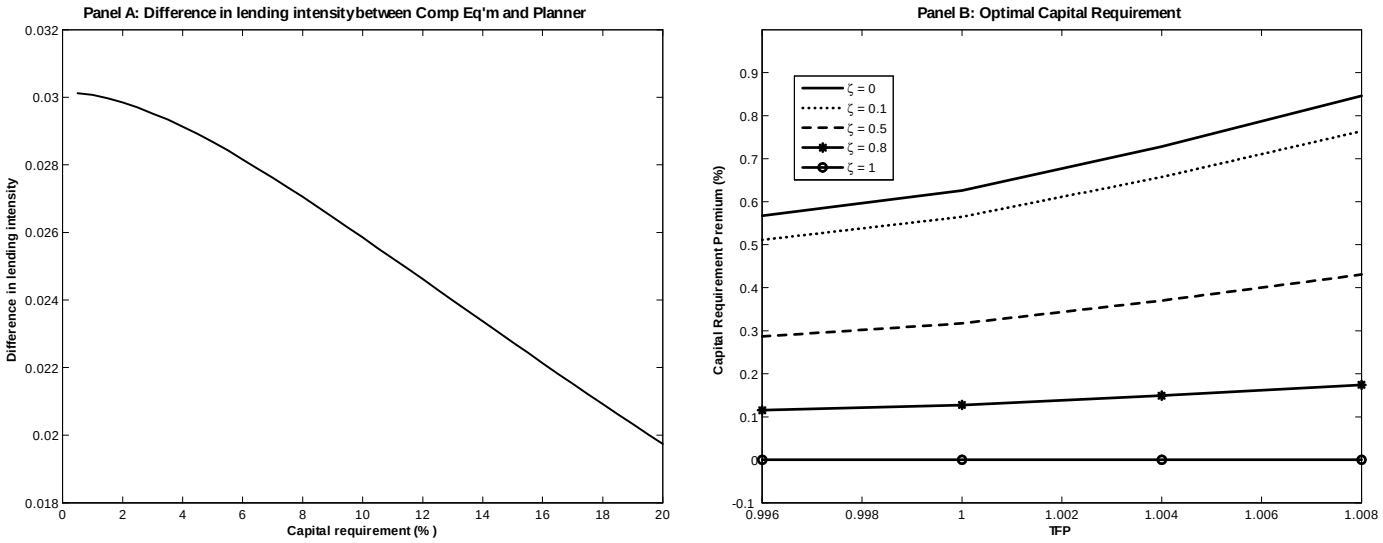

Figure 4: Optimal Capital Requirements. Panel A plots the difference between the lending intensities of the Planner and the Competitive Equilibrium as a function of the capital requirement. Given the 4% capital requirement used in the calibration, Panel B plots the addition to that capital requirement needed such that both the Planner and Competitive Equilibrium choose the same lending intensities, as a function of firms' TFP (quality of the borrower pool), for different levels of banking competition (different values of ζ in equation 11). Panel B was computed using the simulations explained in footnote 8.