ESSAYS ON BANKING

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ABSTRACT

The aim of this dissertation is to investigate the macroeconomic performance and welfare consequences of complex banking structures (banking complexity) across two dimensions: liquidity and investment complexity. The first chapter provides an overview of the financial and macroeconomic literature related to banking and how information affects the macroeconomy. The second chapter presents a theoretical framework generalizing banking complexity by endogenizing the salvage value of failed investments by a joint information production function. Several hypotheses are postulated from the framework. First, higher banking complexity acts a stabilizer for small economic shocks suggesting macroeconomic resilience. Second, higher banking complexity acts as an amplifier for large economic shocks suggesting macroeconomic fragility. Lastly, higher investment complexity preserves the stabilizing properties for complex banking. The third chapter empirically tests the hypotheses with matched bank-firm US syndicated loan data which remains broadly consistent with all three hypotheses.

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CHAPTER 1

INTRODUCTION

Banking is increasingly a complex activity. In the early 1980s, the typical bank loan involved the interaction between a single banking institution and a client firm. Since then, at least two major developments have radically transformed the complexity of banking activities. First, loans have frequently turned into multilateral financing arrangements in which groups of banks cooperate in granting funds to a firm borrower; that is, an expansion of the syndicated loan market. In a syndicated loan, multiple lenders cooperate in the collection of information on the prospects of a would-be borrower. Second, the organizational structure of many banks have transformed from being an elementary institution acting independently to becoming affiliates of a complex banking conglomerate. These trends are shown in Figures 1 and 2 which plot, respectively the aggregate US syndicated loans outstanding from 2009 to 2021 and the degree of concentration of US banking institutions over the 1994-2019 period.

While the microeconomic implications of banking complexity have received growing attention, relatively little is understood of the macroeconomic consequences. In this dissertation, I study the aggregate implications of banking complexity focusing on a core dimension of banking; the production and sharing of credit market information. The premise of our analysis is that the information produced by banks has typically a twofold nature. On the one hand, it helps banks build knowledge about borrowers' activities and assets. This enables banks to better extract value from borrowers' assets, such as better repossessing and liquidating their collateral assets in the event of default. On the other hand, the information produced by banks also helps them better understand the prospects of clients, possibly allowing banks to withdraw financing in a timely manner when borrowers' prospects deteriorate. These two dimensions of information are (partially) non-separable: understanding the characteristics and evolution of the assets of a borrowing firm also helps detect a deterioration of the firm's projects.

With this premise in mind, I consider two modes of organization of banking. Under "elementary banking", information production on a firm's assets is performed by a single banking institution. When a second bank (henceforth, "the late agent") is invited to participate in the financing, this participant is merely a liquidity provider with no active role in acquiring information on the firm's assets. Under "complex banking", information production on a firm's assets is instead a joint effort of multiple institutions. In particular, the loan originator, while retaining an advantage in understanding the borrower's prospects, can involve a second participant bank in assisting to monitor the borrower's collateral assets. This comes at a risk, however: as a by-product of its monitoring activity the participant bank can obtain information about the prospects of the borrowing firm and, if this information is unfavorable, it can withdraw its liquidity and support to the monitoring endeavor. I generalize these two modes of organization of banking as a continuum, parameterized by the degree of banking complexity.

I examine the resilience to aggregate shocks of banking regimes characterized by different degree of complexity. We further investigate how investment informational opacity and bank liquidity status shape the link between banking complexity and macroeconomic resilience. We show that by enabling the cooperation of multiple banks in the monitoring process, greater banking complexity results in better resilience to shocks as long as aggregate economic conditions remain relatively good (e.g., small recessionary shocks leading to low investment default probabilities). In this scenario, banks need to produce a relatively small amount of information on firms' collateral assets. The risk that participant banks learn unfavorable information as a by-product of their cooperation to monitoring is thus limited. As a result, the benefits of banks' monitoring coordination dominates any risk that participating banks learn unfavorable information. However, when economic conditions are poorer (the economy is hit by large recessionary shocks), the probability that projects default is higher and banks tend to produce more information on collateral assets. In this scenario with large information production, there is a large risk that participant acquire unfavorable information about borrowers' investment prospects. This risk rises with the degree of banking complexity.

I find that, following large recessionary shocks, loan originating banks can react to the risk of information disclosure in two ways. If projects are sufficiently transparent, they will react by significantly intensifying the production of information on borrowers' assets (over-monitoring). The resulting boost to collateral asset values will deter information acquisition on project quality by participant banks as higher collateral values will offer them protection. If instead projects are opaque then any attempt by loan originators to produce more information will release significant information on project quality to participant banks. Hence, loan originators will prefer undermonitoring, resulting in a stronger contraction of collateral values and credit . In this latter scenario, therefore, greater banking complexity will lead to greater fragility to aggregate shocks.

I first characterize in closed form the effects of shocks under different banking complexity regime and then perform numerical simulations to quantify the magnitude of the effects. In the second part of the model, we embed our setup in a dynamic framework featuring a stylized process of banks' information accumulation. We show that the model can generate rich dynamics following persistent shocks. In particular, we find that complex banking regimes can reduce the negative output response in the immediate aftermath of a shocks, but slow down the subsequent output recovery. That is, complex banking can generate a dynamic trade-off between the depth and the length of a recession.

Additionally, I test the predictions of the model using matched bank-firm data from the United States. Leveraging information from the Thomson Reuters DealScan database on syndicated loans extended in the US credit market in the period 1987-2013, I construct proxies for the complexity of the bank lending pools that extended financing to firms. I then match the DealScan data with the Bureau Van Dick Compustat database to measure firms' response to different types of aggregate shocks occurred during the 1987-2013 period. Consistent with the predictions of the theoretical model, the estimates reveal that more complex bank lending pools (characterized by banks' joint information production) enhance the resilience of firms to relatively small negative shocks but tend instead to amplify the drop in firms' assets and investment growth in the aftermath of large shocks. In additional tests, I also uncover evidence that the amplifying effect of banking complexity is especially pronounced when firms' investments can be harder to understand for third parties (informationally opaque), again consistent with the model's predictions.

1.1 Prior Literature

The dissertation relates to various strands of literature on the influence of banks on real economic activity. A first broad literature studies the role of banks in producing and transmitting information (Section 1.1.2). The second related literature investigates the role of credit market information in attenuating or amplifying exogenous shocks (Section 1.1.3). Finally, the dissertation relates more broadly to the literature on the implications of banking complexity and investment complexity (Section 1.1.4).

1.1.1 Bank Information

A recent strand of studies highlight that banks can conceal information on the fragility of projects, thereby raising the liquidity of fragile investments. In Gorton and Ordonez (2014) banks insure investors against premature liquidity shocks by raising funds from patient (late) agents. Raising funds at intermediate stages may however require increasing the informational opaqueness of investments, and banks have a superior advantage in this technology relative to dispersed capital markets. Gorton and Ordonez (2020) examine the implications of this role of banks for business cycle transmission. This recent strand of studies introduces a new perspective relative to the more traditional view of banks as superior producers of information. In Diamond and Rajan (2001) and Diamond and Rajan (2002) for example, banks' information raises the salvage value of investments in case of investment failure. In our analysis, we take a step towards bridging these two views of banks' information and study the implications for output and welfare. In doing so, we differentiate across banking structures characterized by different effectiveness in producing and hiding information. In particular, we show that banking complexity stimulates joint production of information but increases the risk the information percolates across banking institutions.

1.1.2 Credit Market Information

A growing body of studies show that banks can exhibit a countercyclical propensity to produce information (Asea and Blomberg, 1998; Ruckes, 2004; Lisowsky et al., 2017; Becker et al., 2020; Cao et al., 2020; Gustafson et al., 2021). This countercylicality of bank monitoring has been shown to influence the cyclical behavior of credit (Becker et al., 2020; Cao et al., 2020), unemployment (Asea and Blomberg, 1998), and bank price competition (Ruckes, 2004). We share the view of these studies regarding the cyclicality of bank information production and incorporate this into a model of banking structures to investigate their consequences for macroeconomic stability.

1.1.3 Implications

In Gai et al. (2011); Caballero and Simsek (2013); Elliott et al. (2014); Acemoglu et al. (2015); Cabrales et al. (2017) banking complexity relates to the density of connections across independent banks while our focus is on the complexity of banks' information production process. Despite a different focus and approach, we share with the above studies the emphasis on the consequences of banking complexity for financial fragility (Gai et al., 2011) and resilience (Elliott et al., 2014; Acemoglu et al., 2015). We also study the interaction between banking complexity, investment complexity and bank liquidity. Our notion of investment complexity relates to the empirical literature examining the design of loan agreements (Ganglmair and Wardlaw, 2017; Ivashina and Vallee, 2020) and securitization of loans (Keys et al., 2010). Ganglmair and Wardlaw (2017) suggests that for firms closer to default the detail and customization of loan agreements grows. Lastly, the role of liquidity in banking and its macroeconomic impacts have been examined by: Dutta and Kapur (1998), Holmström and Tirole (1998), Farhi et al. (2009), Gertler and Kiyotaki (2015), Gennaioli et al. (2014), Farhi and Tirole (2021). Within our framework, bank liquidity plays a key role in altering the information production decisions of banks and the relative performance of banking structures of different complexity.

The remainder of the dissertation is organized as follows. In Chapter 2, I present both the static and dynamic model, study its equilibrium, examine the impact of banking structures on macroeconomic stability and welfare implications. Additionally, we perform numerical simulations for the effects of shocks. Chapter 3 presents empirical evidence on the theoretical predictions using matched bank-firm data from the US credit market. Chapter 4 concludes.

CHAPTER 2

MODEL

2.1 Environment

In congruence with Dang et al. (2017), consider a three period economy with a firm, an early agent, a bank, and a late agent. The firm enters the economy in period 0 with a project that requires an amount ω of an endowment good and takes two periods to be implemented. If the project succeeds, an event with probability λ, it produces x units of goods, where $\lambda x > \omega$. If the project fails, it generates a salvage value, measured in units of the endowment good. The early agent enters the economy in period 0 with an amount e of the endowment good. She obtains utility $c_1 + \tau \min\{c, c_1\}$ from consumption in period 1 and utility c_2 from consumption in period 2. This function captures an insurance need of the early agent in period 1. The late agent enters the economy in period 1 with an amount e of the endowment good. He obtains utility c_2 from consumption in period 2. The firm has no endowment and it needs to raise funds to implement the project. It does so by issuing a claim contingent on the future outcome of the project.

I assume that, if the claim issued to fund the project is purchased by the early agent without the intermediation of the bank, the late agent can costlessly acquire information about the future outcome of the project. Information about a project that will fail in period 2 is damaging in case its salvage value is low, since it will prompt the late agent to refuse the claim issued by the firm. However, if the bank purchases the claim and issues debt to the early agent, the late agent must incur a cost in order to observe the future outcome of the project. The presence of the bank is thus beneficial because it produces an opaque debt, making it costly for the late agent to acquire information about the future outcome of the project.

I assume that the salvage value of the project is affected by monitoring efforts exerted by the bank and by the late agent. Precisely, if the bank exerts a monitoring effort μ_B, incurring disutility $\frac{1}{2}\mu_B^2$, and the late agent exerts a monitoring effort μ_L, incurring linear disutility

μ_L, the salvage value of the project is given by $s(\mu_B, \mu_L) = s\mu_L^{\alpha}\mu_B^{1-\alpha}$, where $\alpha \leq \frac{1}{2}$. I also assume that the cost incurred by the late agent in order to observe the future outcome of the project is given by $\frac{\gamma}{\mu_L+1}$, and is thus decreasing in the monitoring effort of the late agent. The parameters α and γ are key in our analysis. I interpret the former as capturing the complexity of the banking structure, and of the latter as capturing investment complexity and, hence, opaqueness.

The sequence of events unfolds as follows. At the beginning of period 0, the bank offers a take it or leave it contract (s_B^g, s_B^b) to the firm. This contract establishes that the bank will fund the project in period 0 and, in period 2, will obtain a payment of s_B^g in case the project succeeds and a payment of s_B^b in case the project fails. After the contract between the bank and the early agent is signed, the bank chooses its monitoring effort μ_B and offers a take it or leave it contract (r_E^g, r_E^b) to the early agent in exchange for her endowment. This contract establishes that the bank will fully insure the early agent, by giving her c units of goods in period 1, and will make contingent payments (r_E^g, r_E^b) in period 2. At the beginning of period 1, the late agent chooses his monitoring effort μ_L. After that, Nash bargaining determines the contract (r_L^g, r_L^b) between the bank and the late agent, where the bargaining power of the bank is θ, where $\theta > \frac{1}{2}$. This contract sets the payment (r_L^g, r_L^b) that the bank will give to the late agent in period 2, in exchange for his endowment in period 1. Finally, in period 2, the outcome of the project is realized and the contracted terms are implemented.

Throughout the analysis, I assume

$$A1 : \max\{\omega, c\} < e < \omega + c.$$

This assumption ensures that the endowment of the early agent is not sufficient to fund the project and, at the same time, insure the early agent in period 1. However, the combined endowments of the early and the late agent are sufficient to cover both needs.

2.1.1 Contracts

In the contract between the bank and the firm, take it or leave it offer by the bank implies that the contract satisfies

$$(s_B^g, s_B^b) = (x, s(\mu_B, \mu_L)).$$

The bank funds the project and extracts its entire revenue, which will be realized in period 2. In turn, in the contract between the bank and the early agent, the key feature is that the early agent is insured in period 1, offered a non-contingent consumption c. This implies that, in period 2, if the project fails, the bank has assets

$$\overline{A}_b = 2e - (\omega + c) + s(\mu_B, \mu_L),$$

while if the project succeeds, the bank has assets

$$\overline{A}_g = 2e - (\omega + c) + x,$$

where I take into account that the bank collected $2e$ goods, used ω to fund the project in period 0, and c to redeem the claim of the early agent in period 1. The early agent is willing to deposit with the bank in period 0 if and only if

$$(1 + \tau)c + \lambda r_E^g + (1 - \lambda)r_E^b \geq e + \tau c, \tag{2.1}$$

since she can always refuse the contract and consume the endowment. Take it or leave it offer by the bank implies that (2.1) binds. Moreover, it is weakly optimal to set

$$r_E^{b*} = 0,$$

which implies

$$r_E^{g*} = \frac{e - c}{\lambda}.$$

This repayment scheme ensures that the early agent does not get paid in period 2 if the project fails. As it will become clear, this allows to increase the compensation of the late agent in period 2 in case the project fails, thus reducing his incentive to acquire information about the outcome of the project. The assets of the bank after payment to the early agent are given by

$$A_b = 2e - (\omega + c) + s(\mu_B, \mu_L)$$

if the project fails, and

$$A_g = 2e - (\omega + c) + x - \frac{e-c}{\lambda}$$

if the project succeeds.

In what follows I take the monitoring efforts of the bank and the late agent as given and determine their contract. Moreover, I assume that the bank holds the belief that the late agent will not acquire information about the outcome of the project. In the next subsection, I make sure that this belief is consistent with the actual choices of monitoring efforts by the bank and the late agent.

If a contract is signed between the bank and the late agent, the bank obtains $\lambda\left(A_g - r_L^g\right) + (1-\lambda)\left(A_b - r_L^b\right)$ and zero otherwise. In fact, failure to sign implies that the bank will only have $e-\omega$ units of goods in period 1. Since $e-\omega < c$, the bank will be liquidated because it will not have enough resources to fulfill its contract with the early agent. In turn, the payoff of the late agent in case he signs the contract is $\lambda r_L^g + (1-\lambda) r_L^b$, and e otherwise. Bargaining between the bank and the late agent then solves

$$\max_{r_L^g \geq 0, r_L^b \geq 0} \left\{ \left[2e - (\omega + c) + \lambda\left(x - \frac{e-c}{\lambda}\right) + (1-\lambda)s(\mu_B, \mu_L) - r_L \right]^{\theta} \left[r_L - e\right]^{1-\theta} \right\},$$

where $r_L \equiv \lambda r_L^g + (1-\lambda) r_L^b$ is the expected payoff of the late agent. I need to make sure that the bank has enough resources for each outcome realization of the project, i.e., I need

$$A_g \equiv 2e - (\omega + c) + x - \frac{e-c}{\lambda} \geq r_L^g, \tag{2.2}$$

and

$$A_b \equiv 2e - (\omega + c) + s(\mu_B, \mu_L) \geq r_L^b. \tag{2.3}$$

Observe that, given r_L, it is optimal to set (2.3) at equality. This increases the region where (2.8) and (2.2) holds, with no impact on the maximand, which only depends on r_L. I have

$$r_L^{b*} = 2e - (\omega + c) + s(\mu_B, \mu_L).$$

Note that assumption A1 implies $r_L^{b*} \geq 0$. In the Appendix, I use r_L^{b*} to rewrite the bargaining problem between the bank and the late agent and show that the solution is interior. This implies that the payoffs of the late agent (π_L) and the bank (π_B) are equal to their outside option plus a share of the surplus commensurate with their bargaining power. Precisely,

$$\pi_L = e + (1-\theta)\left[\lambda x - \omega + (1-\lambda)s(\mu_B, \mu_L)\right],$$

and

$$\pi_B = \theta\left[\lambda x - \omega + (1-\lambda)s(\mu_B, \mu_L)\right].$$

Summarizing, in this subsection I showed that, if the bank holds the belief that the late agent will not acquire information about the outcome of the project, there exists a set of incentive-feasible contracts that ensure the implementation of the project in period 0 and the insurance of the early agent in period 1.

2.1.2 Monitoring

I now take contracts signed in the previous section as given and determine the monitoring efforts of the bank and the late agent. I start with the late agent. He solves

$$\max_{\mu_L \geq 0} \left\{e - \mu_L + (1-\theta)\left[\lambda x - \omega + (1-\lambda)s(\mu_B, \mu_L)\right]\right\}.$$

Using $s(\mu_B, \mu_L) = s\mu_L^{\alpha}\mu_B^{1-\alpha}$, the solution is

$$\mu_L = \left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{1}{1-\alpha}} \mu_B. \tag{2.4}$$

There is strategic complementarity between the monitoring effort of the bank and the monitoring effort of the late agent. In what follows, we are interested in instances where an increase in banking complexity, as captured by α, improves the salvage value of the project, i.e., $\frac{\partial s(\mu_B,\mu_L)}{\partial \alpha} > 0$. This requires $\mu_L > \mu_B$, i.e.,

$$A2 : s > \frac{1}{(1-\theta)(1-\lambda)\alpha},$$

which is henceforth assumed.

I now consider the monitoring effort of the bank. Its expected payoff is $\Pi_B(\mu_B) = -\frac{1}{2}\mu_B^2 + \pi_B$. Using (2.4) and the fact that $\theta(\lambda x - \omega)$ does not interact with μ_B, I can rewrite $\Pi_B(\mu_B)$ as

$$\widehat{\Pi}_B(\mu_B) = -\frac{1}{2}\mu_B^2 + \theta(1-\lambda)s\left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{\alpha}{1-\alpha}}\mu_B. \tag{2.5}$$

Note that $\widehat{\Pi}_B(\mu_B)$ is a concave, symmetric function, with a maximum at

$$\mu_B^* = \theta(1-\lambda)s\left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{\alpha}{1-\alpha}}. \tag{2.6}$$

Moreover, $\Pi_B(0) = \Pi_B(2\mu_B^*) = 0$.

In what follows, I want to ensure that a failed project is never more appealing than a successful one. A sufficient condition is

$$A3 : x > \frac{e-c}{\lambda} + 2\theta(1-\lambda)s^2\left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{2\alpha}{1-\alpha}},$$

which is henceforth assumed.

In the previous section, I claimed that the bank holds the belief that the late agent will not obtain information about the outcome of the project. I now examine the conditions under which this claim is warranted. There are two possible scenarios.

First, we can have $A_g > A_b \geq e$. In this case, the late agent always has an incentive to deposit with the bank. Thus, he has no incentive to acquire information about the outcome of the project as it will not impact his behavior. We obtain that $A_g > A_b \geq e$ if and only if

$$2e - (\omega + c) + s\mu_L^{\alpha}\mu_B^{1-\alpha} \geq e,$$

which, using (2.4), can be rewritten as

$$z \equiv \omega + c - e \leq F(\mu_B) \equiv s\left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{\alpha}{1-\alpha}}\mu_B, \tag{2.7}$$

If $A_g > A_b \geq e$ holds, the bank maximizes (2.5) subject to (2.7).

Second, we can have $A_g > e > A_b$. In this case, the late agent does not deposit with the bank if he learns of a bad outcome. As a result, in order to ensure that the late agent does not have an incentive to acquire information we need

$$\lambda r_L^{g*} + (1-\lambda) r_L^{b*} \geq -\frac{\gamma}{\mu_L + 1} + \lambda r_L^{g*} + (1-\lambda) e. \tag{2.8}$$

Substituting for the values of r_L^{g*} and r_L^{b*} and μ_L, we can rewrite (2.8) as

$$z \leq G_\gamma(\mu_B) \equiv s\left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{\alpha}{1-\alpha}} \mu_B + \frac{1}{1+\left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{1}{1-\alpha}} \mu_B} \frac{\gamma}{1-\lambda}. \tag{2.9}$$

If $A_g > e > A_b$ holds, the bank maximizes (2.5) subject to (2.9). It is easy to see that $G_\gamma(\mu_B) > F(\mu_B)$ for all μ_B. As a result, a necessary and sufficient condition for the bank to choose μ_B^* is that $z \leq G_\gamma(\mu_B^*)$. If $z \leq F(\mu_B^*)$, $A_g > A_b \geq e$ and the bank chooses μ_B^* because the late agent does not care about acquiring information about the project. If $z \in (F(\mu_B^*), G_\gamma(\mu_B^*)]$, we have $A_g > e > A_b$ and the bank chooses μ_B^* because the late agent does not want to incur the cost and acquire information about the project.

It remains to consider the region of parameters where $z > G_\gamma(\mu_B^*)$ and the late agent acquires information about the outcome of the project if the bank chooses μ_B^*. In this case, the information constraint binds and the bank either chooses zero monitoring effort or it chooses $z = G_\gamma(\widehat{\mu}_B)$. In fact since $G_\gamma''(\mu_B) > 0$, $z = G_\gamma(\widehat{\mu}_B)$ determines the bank's monitoring effort that is closest to the unconstrained optimal μ_B^*. Now, the fact that $\widehat{\Pi}_B(\mu_B)$ is concave and symmetric around μ_B^* implies that the constrained optimal solution must satisfy $z = G_\gamma(\widehat{\mu}_B)$. However, we also need to make sure that $\widehat{\mu}_B$ is closest to μ_B^* than zero, otherwise the bank is better off choosing to exert no monitoring effort. Now, the choice $z = G_\gamma(\widehat{\mu}_B)$ is non-trivial because $G_\gamma''(\mu_B) > 0$ implies that $z = G_\gamma(\widehat{\mu}_B)$ may have two positive solutions, $\mu_B^+ > \mu_B^*$ and $\mu_B^- < \mu_B^*$. In the Appendix, I fully characterize the bank's choice as a function of z and γ. This allows an easy comparison with μ_B^*, since μ_B^* does not depend on these parameters. Proposition 1 summarizes our results.

Proposition 1 *For all $z \in (0, e)$, there exists a set of incentive-feasible contracts that ensure the implementation of the project by the firm and the insurance of the early agent. Given these contracts, the late agent chooses $\mu_L = \left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{1}{1-\alpha}} \mu_B$, while the monitoring* *effort of the bank is characterized as follows. There exists* $\underline{\gamma} < \overline{\gamma}$ *such that: (i) for all* $\gamma \leq \underline{\gamma}$, *the bank chooses* μ_B^* *if* $z \leq G_\gamma(\mu_B^*)$, *it chooses* $\mu_B^+(z)$ *if* $z \in (G_\gamma(\mu_B^*), G_\gamma(2\mu_B^*)]$, *and it chooses not to monitor if* $z > G_\gamma(2\mu_B^*)$; *(ii) for all* $\gamma \in (\underline{\gamma}, \overline{\gamma}]$, *the bank chooses* μ_B^* *if* $z \leq G_\gamma(\mu_B^*)$, *it chooses* $\mu_B^+(z)$ *if* $z \in \left(G_\gamma(\mu_B^*), \frac{\gamma}{1-\lambda}\right]$, *it chooses* $\mu_B^-(z)$ *if* $z \in \left(\frac{\gamma}{1-\lambda}, \frac{\gamma}{1-\lambda}\right]$, *and it chooses not to monitor if* $z > \frac{\gamma}{1-\lambda}$; *(iii) for all* $\gamma > \overline{\gamma}$, *the bank chooses* $\mu_B^-(z)$ *if* $z \in \left(G_\gamma(\mu_B^*), \frac{\gamma}{1-\lambda}\right]$, *and it chooses not to monitor if* $z > \frac{\gamma}{1-\lambda}$.

The intuition behind Proposition 1 runs as follows. If z is small and it is relatively cheap to fund the project and insure the early agent, the bank has enough funds to participate in contracts with no need to worry about the incentives of the late agent to acquire information about the outcome of the project. These are instances where the debt produced by the bank is quite insensitive to information. However, when z is larger and funds are tighter, in order to keep producing information insensitive debt, the bank needs to distort its monitoring effort. In particular, two scenarios can arise. The bank may choose to overmonitor in order to boost the salvage value of the project and reduce the temptation of the late agent to acquire information on the failure probability of the project. Alternatively, the bank may choose to undermonitor in order to increase the late agent's cost of acquiring information about the project (recall the complementarity between banks and late agent monitoring).

Proposition 1 implies, for example, that overmonitoring occurs if γ is relatively small while undermonitoring occurs if γ is relatively large, making it easier to increase the late agent's cost of information acquisition. Interestingly, if γ assumes intermediate values, there is a discontinuity of the bank's monitoring at $z = \frac{\gamma}{1-\lambda}$. If $z < \frac{\gamma}{1-\lambda}$, μ_B converges to μ_B^+ when z converges to $\frac{\gamma}{1-\lambda}$, while if $z > \frac{\gamma}{1-\lambda}$, μ_B converges to μ_B^- when z converges to $\frac{\gamma}{1-\lambda}$. Thus, if $z \approx \frac{\gamma}{1-\lambda}$, a small increase in z can cause a discrete change from over monitoring to under monitoring. This change causes a substantial drop in the salvage value of the project, which is reinforced by the complementarity between the monitoring effort of the bank and that of the late agent. Figure 3 provides an abstract illustration of Proposition 1.

2.2 Complexity and Macroeconomic Outcomes

In what follows, I study the response of output to changes in economic conditions. In particular, I am interested in how changes in the probability of project success (λ) affect output (y), and how these effects depend on the degree of banking complexity (α) and investment complexity (γ). In this section I study this question in our static setting and in the next section I consider a dynamic setting.

Output is given by

$$y\left(\alpha,\lambda\right) = \lambda x + (1-\lambda)s(\mu_B,\mu_L), \tag{2.10}$$

that is, it equals the weighted sum of the output in case of success and of the salvage value in case of failure, weighted by the probabilities of success and failure, respectively. Using (2.10), the effect of economic conditions on output is given by

$$\frac{\partial y}{\partial \lambda} = x - s(\mu_B,\mu_L)\left(\frac{1}{1-\alpha} + \epsilon_{\mu_B,1-\lambda}\right), \tag{2.11}$$

where $\epsilon_{\mu_B,1-\lambda} = \frac{\partial \mu_B}{\partial 1-\lambda}\frac{1-\lambda}{\mu_B}$. The change in the monitoring efforts of the bank and the late agent can mitigate or amplify the output impact of a deterioration in economic conditions (lower λ). In particular, a lower λ directly stimulates the monitoring effort of the late agent, as the late agent will expect a higher probability of project failure. However, a priori, the impact of a lower λ on the monitoring effort of the bank, and hence, by complementarity, the induced monitoring response of the late agent, is ambiguous, that is, $\epsilon_{\mu_B,1-\lambda}$ can be positive or negative. In particular, the sign of $\epsilon_{\mu_B,1-\lambda}$ depends on whether (2.9) binds and the economy is in the constrained information regime, or whether (2.9) does not bind and the economy is in the unconstrained information regime.

In what follows, I first consider intensive margin effects, studying the behavior of monitoring and output when a bank remains in the unconstrained or constrained regions. I then consider extensive margin effects, studying the transition from the unconstrained into the constrained region, particularly how the probability of entering the constrained region depends on economic conditions (λ), banking complexity (α), and investment complexity (γ). Finally, I draw conclusions for the resilience of output and welfare.

2.2.1 Intensive Margin Effects

I start with the unconstrained region and then consider the constrained information region. If the bank chooses μ_B^*, we have $\epsilon_{\mu_B^*,1-\lambda} = \frac{1}{1-\alpha} > 0$ and worse economic conditions increase the monitoring effort of the bank and the late agent. In turn, using $\epsilon_{\mu_B^*,1-\lambda}$, we obtain

$$\frac{\partial y^*}{\partial \lambda} = x - \frac{2\theta(1-\lambda)s^2}{1-\alpha}\left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{2\alpha}{1-\alpha}},$$

and

$$\frac{\partial^2 y^*}{\partial \lambda \partial \alpha} = -\frac{2\theta(1-\lambda)s^2\left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{2\alpha}{1-\alpha}}}{1-\alpha}\frac{3+2\ln\left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{1}{1-\alpha}}}{1-\alpha}.$$

Assumption A2 implies $\frac{\partial^2 y^*}{\partial \lambda \partial \alpha} < 0$ and an increase in bank complexity always mitigates the response of output to worse economic conditions. Finally, investment complexity has no effect on $\frac{\partial y^*}{\partial \lambda}$ because γ has no impact on monitoring and output in the region where the bank chooses μ_B^*.

Summarizing, in the unconstrained region, the monitoring of the bank and the late agent is more intense when economic conditions are worse, mitigating the impact on output of worse economic conditions ($\epsilon_{\mu_B,1-\lambda} > 0$). This attenuation effect of "countercyclical" monitoring is larger under a more complex banking regime and it is not affected by changes in investment complexity.

In the constrained region, the response of the bank and the late agent monitoring to worse economic conditions can act as an attenuator or as an amplifier. In turn, banking complexity and investment complexity have ambiguous effects on the degree of stabilization.

In fact, we can use $\widehat{\mu}_L = \mu_L\left(\widehat{\mu}_B\right)$ to rewrite $z = G_\gamma(\widehat{\mu}_B)$ as

$$z(1-\lambda) = \frac{\widehat{\mu}_L}{\alpha(1-\theta)} + \frac{\gamma}{\widehat{\mu}_L + 1}.$$

We obtain

$$\frac{\partial \widehat{y}}{\partial \lambda} = x - \frac{\widehat{\mu}_L \epsilon_{\widehat{\mu}_L,1-\lambda}}{(1-\theta)(1-\lambda)\alpha},$$

where

$$\epsilon_{\widehat{\mu}_L,1-\lambda} = \frac{z}{z - \frac{2\widehat{\mu}_L+1}{(\widehat{\mu}_L+1)^2}\frac{\gamma}{1-\lambda}}.$$

Since the sign of $\epsilon_{\widehat{\mu}_L,1-\lambda}$ is ambiguous, monitoring can now change countercyclically, acting as a stabilizer ($\epsilon_{\widehat{\mu}_L,1-\lambda} > 0$) like in the unconstrained regime, or procyclically, acting as an amplifier ($\epsilon_{\widehat{\mu}_L,1-\lambda} < 0$). In what follows I explore these possibilities in the scenario where the bank overmonitors and in the scenario where the bank undermonitors.

We first show that $\epsilon_{\widehat{\mu}_L,1-\lambda} > 0$ when $\widehat{\mu}_L = \mu_L^+$, that is, monitoring is countercyclical and acts as an output stabilizer if the bank overmonitors. To see this, first note that $\epsilon_{\mu_L^+,1-\lambda} > 0$ requires $z > \frac{2\mu_L^+ + 1}{\left(\mu_L^+ + 1\right)^2} \frac{\gamma}{1-\lambda}$. Since $z > G_\gamma(\mu_B^*)$ in the region of parameters where the bank cannot chose μ_B^*, and since $\mu_L^+ > \mu_L^*$, it suffices to show that $G_\gamma(\mu_B^*) > \frac{2\mu_L^* + 1}{\left(\mu_L^* + 1\right)^2} \frac{\gamma}{1-\lambda}$. We can rewrite this inequality as $\gamma < \overline{\gamma}$. Proposition 1 shows that this inequality is necessary for $\widehat{\mu}_L = \mu_L^+$, thus proving our claim that $\epsilon_{\mu_L^+,1-\lambda} > 0$, and that monitoring is countercyclical when the bank overmonitors.

I now examine how changes in banking complexity impacts the response of output to a worsening of economic conditions. After some algebraic manipulation, we can write $\frac{\partial^2 y^+}{\partial\lambda\partial\alpha}$ as

$$\frac{\partial^2 y^+}{\partial\lambda\partial\alpha} = \frac{\mu_L^{+2}}{\left(\mu_L^+ + 1\right)^2} \frac{\mu_L^+ - 1}{\mu_L^+ + 1} \frac{z + \frac{1}{\mu_L^{+2} - 1}\frac{\gamma}{1-\lambda}}{\left[z - \frac{2\mu_L^+ + 1}{\left(\mu_L^+ + 1\right)^2}\frac{\gamma}{1-\lambda}\right]^2} \frac{\gamma \epsilon_{\mu_L^+,1-\lambda}}{(1-\theta)\left[(1-\lambda)\alpha\right]^2}.$$

Assumption A2, together with $\theta > \frac{1}{2}$ implies that $\mu_L^* > 1$. Since $\epsilon_{\mu_L^+,1-\lambda} > 0$, we obtain $\frac{\partial^2 y^+}{\partial\lambda\partial\alpha} > 0$ and an increase in banking complexity amplifies the output response, making it a poor stabilizer.

It remains to consider the impact of investment complexity. We obtain

$$\frac{\partial^2 y^+}{\partial\lambda\partial\gamma} = \frac{z}{\alpha(1-\lambda)(1-\theta)\left(\mu_L^+ + 1\right)^2} \left[\frac{\mu_L^+}{z - \frac{2\mu_L^+ + 1}{\left(\mu_L^+ + 1\right)^2}\frac{\gamma}{1-\lambda}}\right]^2 \frac{\frac{\left(\mu_L^+ + 1\right)^2}{\alpha(1-\theta)} + \gamma}{\frac{\left(\mu_L^+ + 1\right)^2}{\alpha(1-\theta)} - \gamma}. \tag{2.12}$$

Since $z - \frac{2\mu_L^+ + 1}{\left(\mu_L^+ + 1\right)^2}\frac{\gamma}{1-\lambda} > 0$, $\frac{\partial^2 y^+}{\partial\lambda\partial\gamma} > 0$ if and only if $\gamma < \frac{(\widehat{\mu}_L + 1)^2}{(1-\theta)\alpha}$. A sufficient condition is $\gamma < \overline{\gamma}$, which is a necessary condition for the bank to overmonitor. As a result, $\frac{\partial^2 y^+}{\partial\lambda\partial\gamma} > 0$ and an increase in investment complexity amplifies the output response, making it a poor stabilizer.

Consider now the case in which the bank undermonitors, choosing μ_L^- in the information constrained region. Although we do not offer a full characterization, I am able to examine the impact of changes in λ, α, and γ in the region where $z > G_\gamma(\mu_B^*)$ is arbitrarily close to $G_\gamma(\mu_B^*)$. In fact, if $z > G_\gamma(\mu_B^*)$ is arbitrarily close to $G_\gamma(\mu_B^*)$, then $\mu_L^- < \mu_B^*$ is arbitrarily close to μ_B^*, due to the continuity of $G_\gamma(\mu_B)$. As a result, we obtain that $z - \frac{2\mu_L^-+1}{\left(\mu_L^-+1\right)^2}\frac{\gamma}{1-\lambda}$ can be approximated by $G_\gamma(\mu_B^*) - \frac{2\mu_L^*+1}{\left(\mu_L^*+1\right)^2}\frac{\gamma}{1-\lambda}$, which can be rewritten as $\gamma < \frac{\left(\mu_L^*+1\right)^2}{(1-\theta)\alpha}$.

Proposition 1 shows that $\gamma > \underline{\gamma}$ is necessary for $\widehat{\mu}_L = \mu_L^-$. Since $\underline{\gamma} < \frac{\left(\mu_L^*+1\right)^2}{(1-\theta)\alpha}$, we obtain that, if $\gamma \in \left(\underline{\gamma}, \frac{\left(\mu_L^*+1\right)^2}{(1-\theta)\alpha}\right)$, then $\epsilon_{\mu_L^-,1-\lambda} > 0$ and monitoring is countercyclical; while if $\gamma > \frac{\left(\mu_L^*+1\right)^2}{(1-\theta)\alpha}$, then $\epsilon_{\mu_L^-,1-\lambda} < 0$ and monitoring is procyclical. Now, since the sign of $\frac{\partial^2 y^-}{\partial\lambda\partial\alpha}$ is equal to the sign of $\epsilon_{\mu_L^-,1-\lambda}$, we also obtain that, if $\gamma \in \left(\underline{\gamma}, \frac{\left(\mu_L^*+1\right)^2}{(1-\theta)\alpha}\right)$, then $\frac{\partial^2 y^-}{\partial\lambda\partial\alpha} > 0$ and an increase in bank complexity amplifies the output response, making it a poor stabilizer. The opposite happens when $\gamma > \frac{\left(\mu_L^*+1\right)^2}{(1-\theta)\alpha}$.

It remains to examine the impact of changes in investment complexity. It is given by

$$\frac{\partial^2 y^-}{\partial\lambda\partial\gamma} = \frac{z}{\alpha(1-\lambda)(1-\theta)\left(\mu_L^-+1\right)^2}\left[\frac{\mu_L^-}{z - \frac{2\mu_L^-+1}{\left(\mu_L^-+1\right)^2}\frac{\gamma}{1-\lambda}}\right]^2 \frac{\frac{\left(\mu_L^-+1\right)^2}{\alpha(1-\theta)} + \gamma}{\frac{\left(\mu_L^-+1\right)^2}{\alpha(1-\theta)} - \gamma}. \tag{2.13}$$

As in the case of bank complexity, if $\gamma \in \left(\underline{\gamma}, \frac{\left(\mu_L^*+1\right)^2}{(1-\theta)\alpha}\right)$, then $\frac{\partial^2 y^-}{\partial\lambda\partial\gamma} > 0$ and an increase in investment complexity amplifies the output response, making it a poor stabilizer. The opposite happens when $\gamma > \frac{\left(\mu_L^*+1\right)^2}{(1-\theta)\alpha}$. Proposition 2 summarizes our results.

Proposition 2

1. *In the unconstrained information region, monitoring is always a stabilizer, changing countercyclically. In this region, an increase of bank complexity always makes monitoring a better stabilizer, generating a better response of output to worse economic conditions. Investment complexity instead has no effect on the stabilizing properties of bank monitoring.*

2. *In the constrained information region monitoring can still be a stabilizer (changing countercyclically) or become an amplifier (changing procyclically). An increase in bank*

complexity and/or investment complexity will now make any stabilizing effect of bank monitoring weaker (but can also mitigate any amplifying effect of bank monitoring).

2.2.2 Extensive Margin Effects

I have characterized the behavior of bank monitoring and output in the unconstrained and constrained information regions, studying the (de)stabilizing effects of monitoring in response to worse economic conditions, and how bank complexity and investment complexity interact with these effects. I now study whether worse economic conditions tend to push the economy into the constrained information region, and whether banking complexity and investment complexity exacerbate this tendency.

Recall that the region of parameters where the bank chooses μ_B^* satisfies $z \leq G_\gamma(\mu_B^*)$. The frontier of this region as a function of λ, α and γ is then given by $f(\lambda, \alpha, \gamma) = G_\gamma(\mu_B^*)$, i.e.,

$$f(\lambda, \alpha, \gamma) = \theta(1-\lambda)s^2\left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{2\alpha}{1-\alpha}} + \frac{1}{1+\theta(1-\lambda)s\left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{1+\alpha}{1-\alpha}}}\frac{\gamma}{1-\lambda}.$$

We first explore whether worse economic conditions tend to push the economy towards the information constrained region. We obtain that this is always the case, except when the investment complexity is very low. In particular, we can rewrite $f(\lambda, \alpha, \gamma)$ as

$$f(\lambda, \alpha, \gamma) = \frac{1}{1-\lambda}\left[\frac{\mu_L^*}{(1-\theta)\alpha} + \frac{\gamma}{1+\mu_L^*}\right].$$

from which

$$f_\lambda(\lambda, \alpha, \gamma) = \frac{1}{(1-\lambda)^2}\left[\left(1 + \frac{2}{1-\alpha}\frac{\mu_L^*}{1+\mu_L^*}\right)\frac{\gamma}{1+\mu_L^*} - \frac{1+\alpha}{\alpha(1-\alpha)}\frac{\mu_L^*}{1-\theta}\right].$$

As a result, $f_\lambda(\lambda, \alpha, \gamma) > 0$ if and only if

$$\gamma > \widehat{\gamma}(\lambda) = \frac{1+\alpha}{\alpha}\frac{1}{1-\theta}\frac{1+\mu_L^*}{\frac{1-\alpha}{\mu_L^*} + \frac{2}{1+\mu_L^*}}. \tag{2.14}$$

Since $\widehat{\gamma}(\lambda)$ is strictly increasing in μ_L^* and μ_L^* is strictly decreasing in λ, $\widehat{\gamma}(\lambda)$ is strictly decreasing in λ, with an upper bound at $\widehat{\gamma}(0)$ and a lower bound at $\widehat{\gamma}(1) = 0$. This implies that, if $\gamma \geq \widehat{\gamma}(0)$, then $f_\lambda(\lambda,\alpha,\gamma) > 0$ for all λ. If, instead, $\gamma < \widehat{\gamma}(0)$, then there exists $\widehat{\lambda}_\gamma$ such that, for all $\lambda \geq \widehat{\lambda}_\gamma$, $f_\lambda(\lambda,\alpha,\gamma) > 0$; while $f_\lambda(\lambda,\alpha,\gamma) < 0$ for all $\lambda < \widehat{\lambda}_\gamma$.

We next study how the probability of entering the constrained information region when λ drops is affected by bank complexity. We obtain that as long as investment complexity is not too low, higher banking complexity increases the chances of entering the constrained information region when economic conditions worsen. In particular,

$$f_\alpha(\lambda,\alpha,\gamma) = \frac{1}{1-\lambda}\frac{\mu_L^*}{\alpha(1-\alpha)}\left\{\frac{2+\ln\left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{2}{1-\alpha}}}{1-\theta}\right.$$
$$\left.-\gamma\frac{1+\alpha+\ln\left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{2\alpha}{1-\alpha}}}{(1+\mu_L^*)^2}\right\}.$$

We have $f_\alpha(\lambda,\alpha,\gamma) > 0$ if and only if

$$\gamma < \widetilde{\gamma}(\lambda) \equiv \frac{\left\{1+\theta(1-\lambda)s\left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{1+\alpha}{1-\alpha}}\right\}^2}{1-\theta}\frac{2+\ln\left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{2}{1-\alpha}}}{1+\alpha\left\{1+\ln\left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{2}{1-\alpha}}\right\}}.$$

Note that $\widetilde{\gamma}(\lambda)$ is strictly decreasing in λ, with an upper bound at $\widetilde{\gamma}(0)$ and a lower bound at $\widetilde{\gamma}(1) = \frac{1}{(1-\theta)\alpha} = \frac{\gamma^*}{1+\mu_L^*}$. This implies that, if $\gamma \leq \widetilde{\gamma}(1)$, then $f_\alpha(\lambda,\alpha,\gamma) > 0$ for all λ. If, instead, $\gamma \in (\widetilde{\gamma}(1),\widetilde{\gamma}(0))$, then there exists $\widetilde{\lambda}_\gamma$ such that, for all $\lambda \geq \widetilde{\lambda}_\gamma$, $f_\alpha(\lambda,\alpha,\gamma) < 0$; while $f_\alpha(\lambda,\alpha) > 0$ for all $\lambda < \widetilde{\lambda}_\gamma$. Finally, if $\gamma \geq \widetilde{\gamma}(0)$, then $f_\alpha(\lambda,\alpha,\gamma) < 0$ for all λ.

Finally, we examine the impact of investment complexity. We have

$$f_\gamma(\lambda,\alpha,\gamma) = \frac{1}{1+\theta(1-\lambda)s\left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{1+\alpha}{1-\alpha}}}\frac{1}{1-\lambda},$$

and an increase in investment complexity always reduces the probability that the economy enters the information constrained region. Proposition 3 summarizes our results.

Proposition 3 *For a sufficiently high investment complexity, a worsening of economic conditions (decline in λ) pushes the banks monitoring decisions to be constrained. A higher banking complexity exacerbates this effect. A higher investment complexity attenuates this effect by always decreasing the region of parameters where the bank enters the constrained region.*

2.2.3 Taking Stock: Implications for Output Resilience to Small and Large Shocks

The above results yield implications for the output resilience to exogenous economic conditions and for the influence of banking complexity and investment complexity on such resilience.

When shocks are small i.e., for large values of λ, as long as investment complexity is not too low, the economy will remain in the unconstrained information region. Intuitively, bank monitoring will be moderate and there will be no need for banks to be constrained by the need to prevent too much information gathering by the late agent. In this small-shock region, bank monitoring will be countercyclical, stabilizing the economy. Higher banking complexity, in turn, will improve the stabilizing effects of bank monitoring, making the economy more resilient to small shocks.

When shocks become larger, i.e. for lower values of λ, the countercyclical behavior of bank monitoring, and the resulting intensification of information acquisition of late agents, will start to generate a need for banks to hide information on projects. Thus, the economy will enter the information constrained region. As shown above, this happens first for complex banking, just because it tends to stimulate a strongly countercyclical behavior of bank monitoring. It also happens first for less complex investments, which are easier to assess for late agents.

Once the economy enters the information constrained region, bank monitoring can continue to remain countercyclical, acting as a stabilizer. However, the stabilizing properties of banking regimes will flip, with complex banking now diluting the stabilizing effect of countercyclical bank monitoring. An even more dire scenario can occur for large shocks: bank monitoring can become procyclical and hence turn into an amplifier. As complex banking enters first into the constrained region, it is more exposed to this dire scenario.

In conclusion, the analysis predicts that, as long as investment complexity is not too small, complex banking systems are a better stabilizer for small shocks ("better resilience"), but become worse stabilizers, and possibly even amplifiers, for large shocks ("weaker resilience"). I now summarize these patterns with the help of a numerical simulation.

2.2.4 Numerical Simulations

Within the numerical simulations I fix investment complexity (γ) while considering two different liquidity ($z_{\text{low}},\ z_{\text{high}}$) scenarios for two different banking regimes ($\alpha_1,\ \alpha_2$) over a fixed interval of economic conditions (λ). More explicitly, I fix the following parameters: $\theta = 0.5,\ \gamma = 480,\ s = 290,\ x = 8000$, and the λ-region to the interval $[0.97, 0.98]$. With respect to the liquidity parameter I consider a relatively low liquidity state of $z_{\text{low}} = 3550$ and $z_{\text{high}} = 5600$. We can characterize the initial investment ω to be $\omega_1 = 320$ and $\omega_2 = 370$ for each liquidity state resulting in a payoff multiple ranging between 21-25. As Proposition 1 and Figure 3 suggests the variation in liquidity needs by the loan originating bank for a given investment complexity alters the monitoring decision of the loan originating bank once it enters the constrained region by a discontinuous jump. The complexity of the banking regimes is given by $\alpha_1 = 0.35$ and $\alpha_2 = 0.4$. Thus, the α_1-banking regime is less dependent than the α_2-banking regime on participant banks to generate the information necessary to screen potential investments and evaluate their salvage value.

Although this particular simulation takes place in a static setting, our notion of economic shocks and the relative size of those shocks can be considered as a leftward movement along λ where the original economic state is set at $\lambda = 0.98$. We concede our simulations are limited in examining the extensive margin effects as our λ-region does not encompass the entire constrained region of either banking regimes. The emphasis of this section is the intensive margin effects as suggested in Proposition 2. Limited inferences on the extensive margin are made as the simulations highlight the transition points of each banking regime entering the constrained region from the unconstrained.

Figure 5 highlights the scenario when liquidity needs are particularly high (z_{high}). Figure 5 provides a decomposition of $G_\gamma(\mu_B)$ (in reference to equation 2.9) into its salvage value component and its information revelation component. For notational simplicity we label the salvage component and the information revelation component as s and γ (these notations should not be conflated with salvage value shifter nor the investment complexity parameter). More explicitly,

$$
\begin{aligned}
s(\alpha_i) &\equiv s[(1-\theta)(1-\lambda)s\alpha_i]^{\frac{\alpha_i}{1-\alpha_i}}\mu_B, \\
\gamma(\alpha_i) &\equiv \frac{1}{1+[(1-\theta)(1-\lambda)s\alpha_i]^{\frac{1}{1-\alpha_i}}\mu_B}\frac{\gamma}{1-\lambda}, \\
G(\alpha_i) &\equiv s(\alpha_i)+\gamma(\alpha_i),
\end{aligned}
$$

for $i \in \{1, 2\}$.

Figure 5 provides a consistent visualization of the loan originating banks monitoring decisions and its macroeconomic implications. For small economic shocks that leave both banking regimes in a position where informational risks does not pose a serious concern the regime with greater complexity leads to greater economic resilience as the countercyclical information generation attenuates the deteriorating economic conditions. However, for sufficiently large economic shocks the monitoring decisions are altered once both banking regimes enter the constrained region. The high liquidity needs necessitates undermonitoring (procyclical) and thus a rise in opacity as suggested by Figure 5 where $\gamma(\alpha_i)$ is strictly elevated to $s(\alpha_i)$. As a consequence, greater complexity in bank information production leads to excess economic fragility.

Figure 6 portray a different scenario when liquidity needs are low (z_{low}). Similar to the undermonitoring case greater complexity leads to economic resilience for small economic shocks. Unlike the undermonitoring case, the low liquidity requirement alters the banks monitoring decision to engage in overmonitoring once informational risks are serious. We observe in Figure 6 that the salvage value generated by this overmonitoring results elevated $s(\alpha_i)$ versus $\gamma(\alpha_i)$. That is, an excessive rise in transparency resulting in greater economic resilience as bank complexity rises.

We observe for both cases the α_2-banking regime enters the constrained region earlier than the α_1-banking regime. This observation partially vindicates Proposition 3 in the inference that for a sufficiently high investment complexity, greater banking complexity leads to fragility in the sense of entering the constrained region. Since the prime focus is the relationship between investment complexity and banking complexity we relegate the role of liquidity to of secondary importance. Our visualizations are intended to guide the intuition on the relationship between z and α.

2.2.5 Welfare implications

Welfare is given by the output net of monitoring costs,

$$\mathcal{W} = \underbrace{-\frac{1}{2}\mu_B^2 - \mu_L}_{Monitoring\ costs} + \underbrace{\lambda x + (1-\lambda)s(\mu_B, \mu_L)}_{output}.$$

Using (2.4), welfare can be rewritten as

$$\mathcal{W} = -\frac{1}{2}\mu_B^2 + \frac{1-(1-\theta)\alpha}{(1-\theta)\alpha}\left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{1}{1-\alpha}}\mu_B + \lambda x.$$

The bank's monitoring level that maximizes welfare is

$$\mu_B^{\mathcal{W}} = \frac{1-(1-\theta)\alpha}{(1-\theta)\alpha}\left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{1}{1-\alpha}}.$$

Consider first the case in which the economy is in the unconstrained information region. We obtain that $\mu_B^{\mathcal{W}} > \mu_B^*$ if and only if $\theta + (1-\theta)\alpha < 1$, which is always true. Thus, if the information constraint does not bind and the bank chooses μ_B^*, it always monitors less than the welfare maximizing level. This is so because the bank does not internalize the total surplus generated by its effort.

Consider next the case in which the economy is in the constrained information region.(see the Appendix for a full characterization). Since $\mu_B^-(z) < \mu_B^* < \mu_B^{\mathcal{W}}$, it is always the case that welfare decreases once we move from the region where the information constraint does not bind into the region where it binds and the bank undermonitors. A distinct scenario occurs instead if in the constrained information region the bank overmonitors, choosing $\mu_B^+(z)$. In this scenario $\mu_B^* < \mu_B^{\mathcal{W}}$ and $\mu_B^* < \mu_B^+(z)$, so the economy could get closer to the optimal monitoring once we move into the information constrained region (in a knife-edge case, achieving the optimal monitoring). This insight will also turn out to be useful for evaluating the welfare implication of changes in economic conditions.

Finally, it is useful to assess how investment complexity, γ, impacts welfare in the constrained information region. A proof that higher investment complexity implies lower monitoring in this region is available in the Appendix. For example, when the bank overmonitors, we can rewrite $z = G_\gamma(\mu_B^+)$ as

$$z(1-\lambda) = \frac{\mu_L^+}{\alpha(1-\theta)} + \frac{\gamma}{\mu_L^+ + 1}$$

from which

$$\epsilon_{\mu_L^+,\gamma} = -\frac{\frac{1}{\mu_L^+ + 1}\frac{\gamma}{1-\lambda}}{z - \frac{2\widehat{\mu}_L + 1}{\left(\mu_L^+ + 1\right)^2}\frac{\gamma}{1-\lambda}},$$

where we use (2.4) to recover μ_B^+. In the Appendix it is shown that $z > \frac{2\mu_L^+ + 1}{\left(\mu_L^+ + 1\right)^2}\frac{\gamma}{1-\lambda}$. Thus, whenever monitoring lies below the welfare-maximizing one a higher investment complexity and hence a higher cost of acquiring information about projects may hurt welfare by depressing monitoring further below its optimal level. This occurs even though investment complexity contributes to the opacity of projects.

In what follows I assess the impact of economic conditions on welfare, exploiting the above results for output. Consider first the unconstrained information region. In this region, as shown above, output drops as long as

$$\frac{\partial y}{\partial \lambda} = x - s(\mu_B, \mu_L)\left(\frac{1}{1-\alpha} + \epsilon_{\mu_B,1-\lambda}\right) > 0.$$

Recall that welfare is given by output net of the monitoring costs of bank and late agent:

$$\mathcal{W} = -\frac{1}{2}\mu_B^2 - \mu_L + \lambda x + (1-\lambda)s(\mu_B, \mu_L).$$

As proved above, in the unconstrained information region the monitoring of bank and late agent is always countercyclical, so monitoring costs always rise when λ lowers. Together with the output drop this implies that welfare necessarily shrinks in this region, that is, $\frac{\partial \mathcal{W}}{\partial \lambda} > 0$.

One can also study how the gap relative to the welfare-maximizing monitoring changes. We have,

$$\mu_B^{\mathcal{W}} - \mu_B^* = \mu_B^* \frac{(1-\theta)(1-\alpha)}{\theta}.$$

Since in the unconstrained information region μ_B^* rises as λ drops, necessarily $\mu_B^{\mathcal{W}} - \mu_B^*$ rises too and the welfare gap widens.

Welfare effects become more articulated when the economy enters the constrained information region. It is immediate that if in this region the bank undermonitors, then welfare will shrink and the welfare gap will widen. In fact, when there is undermonitoring, banks' monitoring is depressed further below the optimal level. Moreover, optimal monitoring would vary countercyclically and welfare under the optimal monitoring solution would shrink anyway. If the bank undermonitors, monitoring will drop as λ drops (i.e., move procyclically) making the welfare drop even faster than under the optimal solution.

Consider next the case in which banks overmonitor in the constrained information region. As proved above, in this case there will be an improvement in welfare and a narrowing of the welfare gap once the economy enters the constrained region. In fact, the equilibrium monitoring will move closer to the optimal monitoring level.

These welfare consequences are examined using the same parameterizations as in subsection 2.2.4. Figure 7 provides a numerical illustration of the welfare implications of the α_1 and α_2-banking regimes across the two liquidity scenarios. The loan originating banks decision to engage in undermonitoring or overmonitoring in the constrained region provides an appropriate visualization of the welfare consequences. Let us define the welfare gap as

$$\mathcal{NW}(\alpha_i) \equiv \mathcal{W}(\mu_B; \alpha_i) - \mathcal{W}(\mu_B^{\mathcal{W}}; \alpha_i)$$

for $i \in \{1, 2\}$. That is, $\mathcal{NW}(\alpha_i)$ measures the welfare gap between the second-best and first-best monitoring decisions by the loan originating bank for complexity α_i.

Figure 7 highlights when both banking regimes engage in overmonitoring in the constrained region which are related to Figure 6. Counter to the observation of economic resilience as banking complexity rises the welfare consequences suggests an opposite effect. As banking complexity rises welfare declines are amplified as economic conditions deteriorate with an improvement in welfare by the α_2-banking regime only occurring within a certain range of economic conditions as a consequence of extensive margin effects.

Figure 7 also illustrates when both banking regimes engage in undermonitoring in the constrained region associated with Figure 5. An increase in banking complexity amplifies the welfare loss. The difference in welfare losses in the constrained regions between overmonitoring and undermonitoring are consistent with the above derivations. Overmonitoring attenuates the welfare losses while undermonitoring amplifies the welfare losses. Stark comparisons in the welfare implications of complex bank monitoring when subject to different liquidity scenarios are suggested in Figure 7.

2.3 Dynamic Setting

I now extend the economy into an infinite horizon. The environment is largely as in the baseline set up, but now I collapse our three period setting into a one-period economy with two sub-periods. Moreover, to streamline the exposition, I merge the bank and the firm into one entity, that is, the bank gathers funds from agents and implements a project. The project has the same properties as in the three-period economy. At the very beginning of a period, a new bank, a new early agent, and a new late agent enter the economy. The early agent receives her endowment in the first sub-period, while the late agent receives her endowment in the second sub-period. Their preferences replicate those specified in the three-period economy. At the end of a period, the bank, the early agent and the late agent die and, at the beginning of the following period, they are replaced by a new bank, a new early agent and a new late agent.

The distinct feature of the infinite-horizon framework consists of the dynamics of information accumulation. We assume that the salvage value of the project depends not only on the current monitoring efforts of the bank and the late agent but also on the monitoring effort of previous banks. This is meant to capture a notion of accumulation of knowledge or experience over time which is reusable by the following generations. Precisely, in a manner similar to Aliaga-Díaz and Olivero (2010) the salvage value of the project in period t is now given by

$$s(\mu_{Bt}, \mu_{Lt}) = s_t \mu_{Lt}^{\alpha} \mu_{Bt}^{1-\alpha},$$

where, for all $t > 1$,

$$s_t = \rho s \mu_{Bt-1}^{\kappa} + (1-\rho) s_{t-1},$$

and s_0 is given. With $|\rho| < 1$ being a persistence parameter, $s > 0$ being a scale parameter and $\kappa < 1 - \alpha$ being the information generation parameter of past monitoring efforts. We also posit that the probability of project success is given by

$$\lambda_t = \lambda + \varepsilon_t,$$

where λ is the long-run average probability and ε_t denotes a shock in period t.

In every period, the contracts in the dynamic economy are the same as in the three-period economy. In turn, the monitoring effort of the late agent is given by

$$\mu_{Lt} = [(1-\theta)(1-\lambda_t) s_t \alpha]^{\frac{1}{1-\alpha}} \mu_{Bt}.$$

The bank's monitoring choice is also similar. Using the same argument leading to the Proposition 1, the bank's problem can be summarized as

$$\max_{\mu_{Bt}} \left\{ -\frac{1}{2}\mu_{Bt}^2 + \theta(1-\lambda_t) s_t \left[(1-\theta)(1-\lambda_t) s_t \alpha\right]^{\frac{\alpha}{1-\alpha}} \mu_{Bt} \right\},$$

subject to

$$z \leq G_{\gamma,t}(\mu_{Bt}) \equiv s_t \left[(1-\theta)(1-\lambda_t) s_t \alpha\right]^{\frac{\alpha}{1-\alpha}} \mu_{Bt} + \frac{1}{1-\lambda_t} \frac{\gamma}{\left[(1-\theta)(1-\lambda_t) s_t \alpha\right]^{\frac{1}{1-\alpha}} \mu_{Bt} + 1}.$$

If $z \leq G_{\gamma,t}(\mu_{Bt})$ and the information constraint does not bind in period t, the bank's monitoring choice is

$$\mu_{Bt}^{*} = \theta(1-\lambda_t) s_t \left[(1-\theta)(1-\lambda_t) s_t \alpha\right]^{\frac{\alpha}{1-\alpha}}.$$

If, instead, $z > G_{\gamma,t}(\mu^*_{Bt})$, the information constraint binds at μ^*_{Bt}. In this case, if the bank chooses a positive level of monitoring, we have

$$z = G_{\gamma,t}(\mu_{Bt}) \equiv s_t \left[(1-\theta)(1-\lambda_t)s_t\alpha\right]^{\frac{\alpha}{1-\alpha}} \mu_{Bt} + \frac{1}{1-\lambda_t} \frac{\gamma}{\left[(1-\theta)(1-\lambda_t)s_t\alpha\right]^{\frac{1}{1-\alpha}} \mu_{Bt} + 1}.$$

Note that, as in the baseline setting, $G''_{\gamma,t}(\mu_{Bt}) > 0$. This is all we need to adapt the proof of Proposition 1 to the dynamic setting. Proposition 4 summarizes our result.

Proposition 4 *For all $z \in (0, e)$, there exists a set of incentive-feasible contracts that ensure the implementation of the project and the insurance of the early agent. Given these contracts, the late agent chooses $\mu_{Lt} = [(1-\theta)(1-\lambda_t)s_t\alpha]^{\frac{1}{1-\alpha}} \mu_{B_t}$, while the monitoring effort of the bank is characterized as follows. In every period t, there exists $\underline{\gamma_t} \equiv \frac{1+2\mu^*_{Lt}}{\alpha(1-\theta)} < \overline{\gamma_t} = \frac{\left(1+\mu^*_{Lt}\right)^2}{(1-\theta)\alpha}$ such that: (i) for all $\gamma \leq \underline{\gamma_t}$, the bank chooses μ^*_{Bt} if $z \leq G_{\gamma,t}(\mu^*_{Bt})$, it chooses $\mu^+_{Bt}(z)$ if $z \in (G_{\gamma,t}(\mu^*_B), G_{\gamma,t}(2\mu^*_B)]$, and it chooses not to monitor if $z > G_{\gamma,t}(2\mu^*_{Bt})$; (ii) for all $\gamma \in \left(\underline{\gamma_t}, \overline{\gamma_t}\right]$, the bank chooses μ^*_{Bt} if $z \leq G_{\gamma,t}(\mu^*_{Bt})$, it chooses $\mu^+_{Bt}(z)$ if $z \in \left(G_{\gamma,t}(\mu^*_{Bt}), \frac{\gamma_t}{1-\lambda_t}\right]$, it chooses $\mu^-_{Bt}(z)$ if $z \in \left(\frac{\gamma_t}{1-\lambda_t}, \frac{\gamma}{1-\lambda_t}\right]$, and it chooses not to monitor if $z > \frac{\gamma}{1-\lambda_t}$; (iii) for all $\gamma > \overline{\gamma_t}$, the bank chooses $\mu^-_{Bt}(z)$ if $z \in \left(G_{\gamma,t}(\mu^*_{Bt}), \frac{\gamma}{1-\lambda_t}\right]$, and it chooses not to monitor if $z > \frac{\gamma}{1-\lambda_t}$.*

As in the baseline three-period economy, I am interested in examining how shocks to the probability of project success impact on the monitoring effort of the bank and the late agent, on output and on welfare, and how banks' complexity and investment complexity shape these effects. The key difference from the baseline setting is that now the decisions of the current bank and the current late agent depend on past monitoring decisions, since those affect the salvage value. In what follows, to capture these effects, I first describe the monitoring efforts the bank and the late agent exert in the steady state.

In the steady-state equilibrium, $\lambda_t = \lambda$ and $s_t = s^{ss}$. As a result, the bank's monitoring is also constant, given by μ^{ss}_B. Now, we can rewrite s_t as

$$s_t = (1-\rho)^t s_0 + \rho s \sum_{j=0}^{t-1} (1-\rho)^j \mu^{\kappa}_{Bt-1-j}.$$

This implies

$$s_t^{ss} = (1-\rho)^t s_0 + s\left(\mu_B^{ss}\right)^\kappa \left[1-(1-\rho)^t\right].$$

Note that, in order for s_t^{ss} to be constant, we need $s_0 = s\left(\mu_B^{ss}\right)^\kappa$, which we henceforth assume. If the information constraint does not bind in the steady-state, we have

$$\mu_B^{ss} = \left[\theta(1-\lambda)s\right]^{\frac{1-\alpha}{1-\alpha-\kappa}} \left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{\alpha}{1-\alpha-\kappa}},$$

and

$$\mu_L^{ss} = \left[\theta(1-\lambda)s\right]^{\frac{1-\alpha+\kappa}{1-\alpha-\kappa}} \left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{1+\alpha-\kappa}{1-\alpha-\kappa}}.$$

To ensure that, as in Assumption A2, an increase in banking complexity improves the salvage value of the project, we need $\mu_L^{ss} > \mu_B^{ss}$, i.e.,

$$\left[\frac{\theta}{(1-\theta)\alpha}\right]^{\frac{\kappa}{1-\alpha-\kappa}} s > \frac{1}{(1-\theta)(1-\lambda)\alpha},$$

which is implied by A2. Note that, if $\kappa = 0$, μ_B^{ss} and μ_L^{ss} are equal to the unconstrained levels in the three-period economy. In turn, μ_B^{ss} and μ_L^{ss} are strictly increasing in κ and converge to infinity when κ converges to $1-\alpha$. This implies that, there exists $\overline{\kappa} \in (0, 1-\alpha)$ such that $z \leq G_\gamma(\mu_B^{ss})$ for all z, i.e., if κ is large enough, the information constraint never binds in the steady-state. In order to ensure that this is the case, henceforth we assume that $\kappa \geq \overline{\kappa}$.

We can now examine the effect of shocks to the probability of project success. For example, consider a scenario where the economy is in the steady-state equilibrium and a one-time negative shock hits the probability of project succes in period t in such a way that $z > G_\gamma(\mu_B^{ss})$. As a result, the economy enters the region where the information constraint binds, and the bank's monitoring satisfies

$$z = s^{ss}\left[(1-\theta)(1-\lambda_t)s^{ss}\alpha\right]^{\frac{\alpha}{1-\alpha}} \mu_{Bt} + \frac{1}{1-\lambda_t}\frac{\gamma}{\left[(1-\theta)(1-\lambda_t)s^{ss}\alpha\right]^{\frac{1}{1-\alpha}} \mu_{Bt}+1}. \tag{2.15}$$

Note that s^{ss} is the same as the economy was in the steady-state up to the previous period. We can rewrite (2.15) as

$$z = s\left(\mu_B^{ss}\right)^\kappa \left[(1-\theta)(1-\lambda_t)s\left(\mu_B^{ss}\right)^\kappa\alpha\right]^{\frac{\alpha}{1-\alpha}} \mu_{Bt} + \frac{1}{1-\lambda_t}\frac{\gamma}{\left[(1-\theta)(1-\lambda_t)s\left(\mu_B^{ss}\right)^\kappa\alpha\right]^{\frac{1}{1-\alpha}} \mu_{Bt}+1}.$$

The bank's monitoring critically depends on μ_B^{ss}. For example, if $z \in \left(\frac{\gamma_t}{1-\lambda_t}, \frac{\gamma}{1-\lambda_t}\right]$ and the bank chooses to undermonitor, the higher the value of μ_B^{ss}, the lower the monitoring of the bank. In contrast, if $z \in \left(G_{\gamma,t}(\mu_{Bt}^*), \frac{\gamma_t}{1-\lambda_t}\right]$ and the bank overmonitors, the higher the value of μ_B^{ss}, the higher the monitoring of the bank. A numerical illustration that highlights these observations are discussed below.

2.3.1 Numerical simulations

Within the dynamic setting I am able to examine the macroeconomic consequences of both intensive and extensive margin effects and their interactions. Similar to the previous numerical simulations in the static setting we consider two banking regimes ($\alpha_1,\ \alpha_2$). Unlike the static setting, I keep the liquidity parameter z fixed and consider three recessionary shock processes $\{\varepsilon_{it}\}$ with i indexing the particular shock process in question (initial shock period occurs in period 0). More explicitly, I consider the following parameterizations: $\theta = 0.5$, $\alpha_1 = 0.35$, $\alpha_2 = 0.40$, $\kappa = 0.2$, $\rho = 0.2$, $\lambda = 0.98$, $s = 235$, $\gamma = 430$, $z = 4600$, and $x = 16000$.[1] The shock processes are given as:

$$\{\varepsilon_{1t}\} = \{\epsilon_{10} = -0.025\lambda,\ \varepsilon_{11} = -0.025\lambda,\ \varepsilon_{12} = -0.001\lambda,\ \varepsilon_{13} = -0.0005\lambda\}\,;$$

$$\{\varepsilon_{2t}\} = \{\varepsilon_{20} = -0.0005\lambda\};$$

$$\{\varepsilon_{3t}\} = \{\varepsilon_{30} = -0.014\lambda\}.$$

Figure 8 provides the impulse response functions (percentage deviation from steady state) for bank monitoring, salvage value, and output across all three shock processes with an associated supplementary graph of $G(\mu_{Bt}^*)$ which indicates in which period the bank is constrained. With respect to each graph, the α_1-banking regime is represented in red while the α_2-banking regime is represented in black. The first row labeled "Intensive/Extensive Margin" presents the simulations of $\{\varepsilon_{1t}\}$ while the one time shock process $\{\varepsilon_{2t}\}$ is associated with the "Intensive Margin (Undermonitoring)" row. Finally, the one time shock process $\{\varepsilon_{3t}\}$ is highlighted under the "Intensive Margin (Overmonitoring)" row. As suggested above the magnitude and

[1]The dynamic equivalent of Assumption A2 holds over the entirety of our simulation.

sequence of recessionary shocks alters both the timing when bank monitoring becomes constrained and what constrained monitoring decision is undertaken. These observations serves as a prelude of the role of bank complexity to economic fragility and resilience that will be discussed below.

The shock process $\{\varepsilon_{1t}\}$ considers a prolonged severe recessionary shock with two periods of adjustments that occur rapidly. The initial shock is sufficiently large such that both banking regimes pass beyond the constrained region. As Section 2.2 suggests there exists a certain range for γ such that this is possible. We consider such a parameterization in the dynamic setting as the inferences for resilience and recovery qualitatively differ to the static setting. As both banking regimes initially engage in countercyclical monitoring the Output table portrays the greater macroeconomic resilience of the α_2-banking regime. This resilience falters as recovery commences. As a consequence of the excess information generated by the α_2-banking regime the persistence of previous information creates informational risks as observed by the α_2-banking regime entering the constrained region upon economic recovery. The α_2-banking regime engages in undermonitoring resulting in a slower recovery than the α_1-banking regime. Thus, in the presence of persistent information generation, greater banking complexity leads to greater resilience of large recessionary shocks but slower recoveries.

The next two subsections of Figure 8 highlights the intensive margin effects when both banking regimes are subject to the shock processes $\{\varepsilon_{2t}\}$ and $\{\varepsilon_{3t}\}$, respectively. We observe the relative magnitude of the initial shock alters the constrained monitoring decision by the banks with a proclivity to engage in undermonitoring for smaller recessionary shocks. Consistent with the static setting, a rise in bank complexity amplifies the initial shock and leads to slower economic recovery in the presence of undermonitoring. Unlike the static setting, the overmonitoring case presents a different outcome. We observe greater bank complexity results in less overmonitoring information production. As a consequence, the α_2-banking regime is more fragile than the α_1-banking regime. However, as recovery commences the persistence of information generation results in an overshoot in economic output which declines with time.

The presence of persistence in information serves as the key distinction between the dynamic and static settings. In the dynamic setting, the magnitude and longevity of economic shocks play a key role in assessing the macroeconomic implications. The previous derivations combined with the numerical simulations for both the static and dynamic settings creates several hypotheses of banking and investment complexity, respectively. Chapter 3 provides empirical evidence and tests the assertions made.

CHAPTER 3

EMPIRICAL EVIDENCE

We empirically examine the implications of banking structures to the response of business sector to shocks. Based on the predictions of the theoretical model our goal is two-fold. We aim at investigating whether the effects of (negative) aggregate shocks on firm-level indicators of asset and investment growth depend on the complexity of the bank-lending pools from which firms obtain financing. In turn, we are also interested whether this influence of banking complexity on firms' response to shocks differs according to the magnitude of the shocks. Consistent with the model, we interpret banking complexity as instances in which banks' monitoring activity takes the form of a joint monitoring effort of multiple banking institutions rather than being performed by a unique lending bank.

To carry out the empirical analysis, we resort to matched bank-firm data from the United States. We draw and match information from four main sources. The first source consists of the Thomson-Reuter's LPC DealScan database which provides detailed information on syndicated loans extended by banks to firms. As we detail below, syndicated lending is an ideal setting to construct measures of the complexity of bank lending pools. The second data source is the Standard and Poor's Compustat data set, which offers rich information on indicators of firm asset and investment growth. Third, we obtain information on banks from the FDIC Call Report files. Finally, we rely on various official sources for the measurement of aggregate shocks that hit the economy. The period of interest of our empirical tests is dictated by data availability and spans from 1989Q1 to 2015Q4.

In what follows, we detail the data sources, the measurement of the key variables used in the empirical analysis, and the empirical methodology. We then turn to the empirical findings.

3.1 Setting, Measurement, and Methodology

The syndicated lending market is an ideal empirical laboratory for our purposes. Syndicated lending represents a sizeable portion of the total bank credit to non-financial firms

(Sufi, 2007). Moreover, the structure of syndicated loans offers a suitable way to construct proxies for banks' joint effort in monitoring borrowing firms (banking complexity). The arrangement of a syndicated loan generally follows these steps. A firm enters a contractual agreement with a bank which acts as the loan lead arranger. The contract between firm and lead arranger specifies the loan size, the covenants of the loan, and whether collateral backs the loan. The lead arranger can then invite other banks to cofinance the loan. These participant lenders can offer suggestions on the syndication process and perform some monitoring activities. The DealScan database offers detailed information on the banks involved in the loan syndicates, their roles, and the share of the loans they retain.

We match the DealScan data with the Standard and Poor's Compustat database to construct proxies for borrowing firms' growth. The matching is performed exploiting the Chava and Roberts' link (Chava and Roberts, 2008). We clean the matched data to exclude instances in which banks' monitoring is unlikely to play a role in firm-level decisions and performance. We first remove loans that are sold in the secondary market after origination (term loans B) because banks do not retain these loans after the syndication (Ivashina and Sun, 2011). We also focus on lead arrangers that consist of banking institutions, excluding loans that are extended by non-banks. We further apply a number of other more technical adjustments, whose details are relegated to the Data Appendix.

Finally, we further match the DealScan data with information from the FDIC call reports, to recover information about the lending banks in the syndicates. After matching the DealScan, Compustat and Call Reports databases, and cleaning the data in the way detailed above, our data set covers about 23,500 loans extended to nearly 5,500 non-financial firms that operate in 64 industries (two-digit SIC) during the 1989Q1-2015Q4 period.

We construct proxies for the complexity of the bank lending pools from which firms obtain financing. As noted, in line with the theoretical model, we are interested in capturing instances in which banks engage in joint information acquisition and monitoring of borrowing firms. The DealScan database is ideal for this purpose given the rich information on the structure of syndicates. We construct two proxies for the complexity of firms' bank lending pools. The first proxy captures the number of previous interactions among the banks involved in the lending syndicate of a firm. We expect the joint monitoring effort of banks to be stronger the more frequently the banks have interacted and collaborated with each other in the past. Indeed, such a measure of prior relationships among banks captures the history of banks in cooperating with each other in the financing of the firm. To generate this proxy, we reconstruct the syndicated loan market on a bank-bank basis and calculate the total number of interactions (co-sharing a loan) on a five-years rolling window without taking into account the roles that the lending banks took in previous loans. This measure assigns a greater overlap of previous interactions when in the syndicate there are banks with a higher number of prior bilateral interactions (loan co-sharing). This measure of bank lending pool complexity is constructed on a bank-level basis.

As a second proxy of joint effort of banks in monitoring a firm, we consider an inverse measure of the concentration of the syndicated loan. The banking literature maintains that the more the loan shares of a syndicate are concentrated in the hands of the lead arranger, the more the monitoring of the borrowing firm will be performed solely by the lead arranger (Sufi, 2007; Becker and Ivashina, 2018). A more diffuse loan syndicate structure signals instead that the task of monitoring the borrower is shared among the different lenders participating in the loan (Sufi, 2007). As an inverse measure of the syndicate concentration, we consider the variable $1 - HHI$, where HHI is the Herfindahl-Hirshmann index of banks' loan shares in the syndicate. This measure of bank lending pool complexity is constructed on a loan-level basis.

We consider different measures of the growth of a firm, our key dependent variable. The first measure consists of the total asset growth of the firm during the first year, two years and three years following the origination of the syndicated loan. The second measure consists of the growth rate of the firm's investments (change of fixed assets) during the first year, two years and three years following the loan origination.

We control for a wide range of time-varying loan and firm characteristics, including the loan maturity, the firm profitability (return on assets), leverage, S&P credit rating, loan spread, and (an indicator for) whether the loan constitutes a refinancing of a prior loan. We also saturate the empirical model with a detailed set of fixed effects. We include loan purpose and loan type fixed effects to capture loan characteristics that could influence the decisions and performance of the firm following the loan extension. We insert bank fixed effects, to capture bank characteristics (such as the bank size or type) that could drive corporate decisions. Further, we include firm fixed effects to absorb firm time-invariant characteristics. Finally, we insert time fixed effects to capture a variety of other aggregate phenomena that occurred during the sample period. In alternate tests, we replace bank and time fixed effects with bank*time fixed effects.

We consider the response of firms to different types of aggregate shocks. We are primarily interested in distinguishing between relatively small aggregate shocks and large aggregate shocks. To achieve a clean distinction, we consider small oil shocks as a proxy for smaller shocks, and the Great Financial Crisis as a proxy for a large shock. Following Kilian and Vigfusson (2017), we construct a proxy for oil shocks as a dummy that equals one whenever the loan is extended in a quarter in which the price of oil exceeds the expected oil price. In robustness checks, we also weight oil shocks by the exposure of the sector of the firm to oil or refined products (with results virtually unchanged). The Great Financial Crisis, in turn, is captured by a dummy equal to one if the loan is extended in a quarter during which the Great Financial Crisis unfolded.

We test the influence of banking complexity on firms' response to aggregate shocks using the following empirical model:

$$\begin{aligned}\text{Firm}_{flt} =& \alpha + \beta \text{Complex}_{bft} + \gamma \text{Shock}_t + \delta(\text{Complex}_{bft} \times \text{Shock}_t) + \eta X_{ft} \\ &+ \zeta Y_{lt} + \mu_b + \mu_l + \mu_{l'} + \mu_f + \mu_t + \epsilon_{flt}.\end{aligned} \tag{3.1}$$

In the empirical model (3.1), Firm_{flt} stands for the percentage growth of the total asset value or fixed asset value of firm f that is granted a loan l in year t; Complex_{bft} is the proxy for the complexity of the bank pool lending of the firm; Shock_t is a measure of aggregate shocks; X_{ft} denotes the vector of firm controls; and Y_{lt} is the vector of loan controls. We saturate the empirical model with bank fixed effects (μ_b), loan type and loan purpose fixed effects (μ_l and $\mu_{l'}$), firm fixed effect (μ_f), and time fixed effects (μ_t). In additional tests, we drop time and bank fixed effects and insert bank*time fixed effects (μ_{bt}). ϵ_{flt} denotes the error term. Throughout the analysis, for all the regressions, we report standard errors clustered at the bank level.

Table 1 reports sample summary statistics. Looking at firms' demographics, the firms are typically medium-sized and large businesses. On average, the growth rate of firms' total assets over the sample period equals -6%, with a sizeable heterogeneity in growth rates across firms (the coefficient of variation, that is, the standard deviation normalized by the mean, is 33%). The mean growth rate of firms' fixed assets (our measure of firm investment) is -5.9%, with an even higher degree of variation across firms. Looking at firms' financing, the average number of banks that lend to a firm in a syndicate is 13. Our proxies for the degree of banking complexity exhibit variation across the sample, with the coefficient of variation of the measure of prior bank-to-bank interactions equalling 20%, and the coefficient of variation of the Herfindahl-Hirshmann of loan shares equal to 60%.

Considering next the incidence of aggregate shocks in the sample, about 8% of the loans are extended during the Great Financial Crisis, while 11.8% of the loans are originated during a negative oil shock episode.

The empirical literature treats the share of the loan retained by the banks participating in the syndicated loan market as a proxy for monitoring incentives (Sufi, 2007; Ivashina, 2009). Figure 9, plots the evolution over time of the average share held by banks and episodes of oil shocks occurred during the sample period. We observe, for example, that during periods of oil shocks (our proxy for small shocks), banks' monitoring increases. Figure 9 reveals a clear positive correlation between shares (monitoring incentives) and oil shocks.

3.1.1 Estimation Results

Tables 2 and 3 show the baseline estimation results. In line with expectations, the estimates consistently point to a negative impact of contractionary aggregate shocks on the growth rate of firms' total assets and fixed assets. This is true both when we consider the proxy for small shocks (oil price fluctuations) and the Great Financial Crisis. Our main interest is in the influence of banking complexity on the resilience of firms to such aggregate shocks. The coefficient estimates on the interaction term (δ) suggest that the complexity of bank lending pools attenuates the negative effect of oil shocks on both firms' asset growth and investment (see columns I, III, V, VII). When we consider, however, the influence of banking complexity on firms' responses to a large negative shock, the GFC, a sharply different picture emerges. As columns II, IV, VI, VIII reveal, more complex bank lending pools appear to amplify the negative response of firms' asset growth and investment to the large shock. As the table shows, the results are robust to the inclusion of different sets of fixed effects, with the statistical and economic magnitude of the coefficients remaining largely unchanged across specifications. The estimates are also robust to considering as dependent variable the average growth of total assets or firms' investment in the two and three years after the loan origination, suggesting that the estimated effects are persistent.

Overall, the empirical results are thus consistent with the key predictions of the theoretical model: banking complexity appears to enhance firms' resilience to small negative aggregate shocks whereas it can reduce firms' resilience to large shocks.

Despite the broad range of loan and firm characteristics and fixed effects included in the specifications, the endogeneity of the bank's complexity to syndicated lending practices may bias the previous estimates. For instance, the same factors that cause individual banks to acquire information via past transactions in certain types of loans could affect syndicated lending practices and alter the loan structure. This issue might bias the effort to directly estimate the effect of bank complexity.

To overcome this identification challenge, we follow Favara and Giannetti (2017) and

Garmaise and Moskowitz (2006) and exploit mergers between banks. Specifically, we focus on mergers between non-failed banks with assets above $1bn that are active in the syndicated loan market. For this purpose, we collect data on M&A from the FRB and identify the banks in DealScan. Then we construct an instrument for bank complexity using only the historical experience variables of the target (acquired) bank, which is mainly outside of the acquiring bank's control. We restrict attention to mergers occurring within a year preceding the origination of the syndicated loan. We also include bank*time, firm, loan purpose and loan type fixed effects, thus effectively exploiting variation within banks while controlling for the firm-loan level demand and the bank's balance sheet.

We exploit variations in our complexity variables that are due to a recent merger. So, we identify a treatment effect using only information from the target bank. The validity of an IV approach depends on the quality of the instruments. Our instruments are likely to satisfy the relevance criterion because a merger constitutes a relevant shock to the acquirer's loan portfolio. When a bank acquires another bank, its portfolio of loans subsequently incorporates the loans that the acquired bank previously extended, thus exogenously broadening the acquiring bank's complexity. In addition, it seems unlikely that the target's complexity affects the acquirer's lending decision due to the timeline of the mergers.

Table 4 shows the results from the two-stages least square estimation with different levels of fixed effects, as reported in the lower part of the table. The first-stage coefficient estimates are displayed in panel A. In columns I-II of the first stage (panel A), we regress the bank complexity proxied by the past interactions on the acquirer's bank complexity and a variety of loan and firm control variables. Similarly in columns III-IV but we use the *1-HHI.* Notably, the sample set of columns I and II is the same, and similar for columns III-IV. The first-stage results confirm a strong and positive relationship between the instrument and bank complexity. Economically, the estimates in column I suggest that a one standard deviation increase in the target's sector experience results in a 10% increase in bank complexity for the acquiring bank. The F-test for excluded instruments support the instrument validity.

The second-stage results (panel B) show that instrumenting for bank complexity generates results qualitatively and quantitatively similar to the baseline specifications. This exercise supports the causal interpretation of our results and the validity of the conclusions drawn from the granular fixed effects. Conditional on the included controls, the endogeneity concerns discussed earlier are not material enough to undermine the interpretation.

As noted in Section 3.2, a distinct prediction of the theoretical model is that banking complexity especially reduces firms' resilience to large negative shocks when firms' investments are less complex and easier to understand for third financing parties. In fact, when firms' investments are easier to understand, a bank will have more incentive and need to hide information from its co-financiers. Based on this prediction, we augment the empirical model accounting for the informational complexity (opaqueness) of firms' investments and for the ease with which investments can be understood by third parties. In particular, we consider the proximity between the loan portfolio of the lead arranger and that of the participant banks. When this proximity is stronger, firms' investments will be easier to understand for participant banks.

Tables 5 and 6 re-estimate the baseline regressions after subsampling firms based on (our proxy for) investment complexity. In line with the theoretical predictions, the estimates reveal that the negative coefficient on the interaction term between banking complexity and large shocks is larger when products are informationally less complex.

Table 7 re-estimates the baseline results restricted to the subsample of firms with relatively lower profitability. We define the threshold for a firm to be included if asset growth falls below the sample median. Panel A uses the past bank-to-bank interactions while Panel B uses the 1-HHI as proxies for bank complexity, respectively. We observe the positive impact of banking complexity is attenuated generally for lower profitable firms when compared to Figures 2 and 3.

In the loan-level analysis, we observe whether bank complexity enhance firms resilience to small negative aggregate shocks and whereas it can reduce firms' resilience to large shocks.

However, the analysis cannot uncover a potential substitution effect and remains silent about real effects. For instance, whether firms can compensate for the loss of credit during large shocks from other banks or whether there are multiple lenders within a syndicate with different levels of complexity that can cancel out the estimated effects.

To test for the substitution and real effects, we aggregate the loan-level data at the firm level and re-estimate the baseline results for up to three years ex-post of shocks. Tables 8 and 9 indicates real effects in the second year and after.

CHAPTER 4

CONCLUSION

4.1 Conclusion and Further Work

This dissertation studies the output and welfare consequences of banks and banking structures in an economy where banks both produce and conceal information on investments. In this setting, more complex banking enables to exploit the benefits of joint information production, raising investments' salvage values, but also increases the risk that information on fragile investments gets disclosed. When economic conditions are relatively good and banks tend to produce limited information, complex banking tends to explicate its output and welfare benefits, enhancing output and welfare resilience to small shocks. When, however, poorer economic conditions call for larger information production, a tension arises within complex banking structures between production and concealing of information. I have found that, as a result of this tension, overall complex banking structures tend to lead to lower resilience to large negative shocks (in contrast with their stabilizing influence following small shocks). However, the degree of their resilience to large shocks crucially depends on the complexity of investments. When investment complexity is large, complex banking structures better retain the ability to mitigate the output and welfare impact of large shocks.

Subsequent future works include exploring the financial contagion implications of complex banking structures. As these structures suggests an interlinking network of liquidity providers an idiosyncratic banking shock may propagate leading to aggregate shocks. Additionally, this dissertation precisely examines the complexity of inter-banking operations. A further examination of the complexity of intra-banking operations by the variety of financial products offered to investors is a possibility. In summary, my dissertation provides a framework in investigating the macroeconomic implications of banking complexity to of which a more refined mechanism can be discussed in the future.

BIBLIOGRAPHY

Acemoglu, D., Ozdaglar, A., and Tahbaz-Salehi, A. (2015). Systemic risk and stability in financial networks. *American Economic Review*, 105(2):564–608.

Aliaga-Díaz, R. and Olivero, M. P. (2010). Macroeconomic implications of "deep habits" in banking. *Journal of Money, Credit and Banking*, 42(8):1495–1521.

Asea, P. K. and Blomberg, B. (1998). Lending cycles. *Journal of Econometrics*, 83(1-2):89–128.

Becker, B., Bos, M., and Roszbach, K. (2020). Bad times, good credit. *Journal of Money, Credit and Banking*, 52(S1):107–142.

Becker, B. and Ivashina, V. (2018). Financial repression in the european sovereign debt crisis. *Review of Finance*, 22(1):83–115.

Caballero, R. J. and Simsek, A. (2013). Fire sales in a model of complexity. *The Journal of Finance*, 68(6):2549–2587.

Cabrales, A., Gottardi, P., and Vega-Redondo, F. (2017). Risk sharing and contagion in networks. *The Review of Financial Studies*, 30(9):3086–3127.

Cao, Q., Di Pietro, M., Kokas, S., and Minetti, R. (2020). Bank monitoring and liquidity in the business cycle. Technical report, Department of Economics, Michigan State University.

Chava, S. and Roberts, M. R. (2008). How does financing impact investment? the role of debt covenants. *The Journal of Finance*, 63(5):2085–2121.

Dang, T. V., Gorton, G., Holmström, B., and Ordonez, G. (2017). Banks as secret keepers. *American Economic Review*, 107(4):1005–29.

Diamond, D. W. and Rajan, R. G. (2001). Liquidity risk, liquidity creation, and financial fragility: A theory of banking. *Journal of Political Economy*, 109(2):287–327.

Diamond, D. W. and Rajan, R. G. (2002). Bank bailouts and aggregate liquidity. *American Economic Review*, 92(2):38–41.

Dutta, J. and Kapur, S. (1998). Liquidity preference and financial intermediation. *The Review of Economic Studies*, 65(3):551–572.

Elliott, M., Golub, B., and Jackson, M. O. (2014). Financial networks and contagion. *American Economic Review*, 104(10):3115–53.

Farhi, E., Golosov, M., and Tsyvinski, A. (2009). A theory of liquidity and regulation of financial intermediation. *The Review of Economic Studies*, 76(3):973–992.

Farhi, E. and Tirole, J. (2021). Shadow banking and the four pillars of traditional financial intermediation. *The Review of Economic Studies*, 88(6):2622–2653.

Favara, G. and Giannetti, M. (2017). Forced asset sales and the concentration of outstanding debt: Evidence from the mortgage market. *The Journal of Finance*, 72(3):1081–1118.

Gai, P., Haldane, A., and Kapadia, S. (2011). Complexity, concentration and contagion. *Journal of Monetary Economics*, 58(5):453–470.

Ganglmair, B. and Wardlaw, M. (2017). Complexity, standardization, and the design of loan agreements. *Available at SSRN 2952567*.

Garmaise, M. J. and Moskowitz, T. J. (2006). Bank mergers and crime: The real and social effects of credit market competition. *The Journal of Finance*, 61(2):495–538.

Gennaioli, N., Martin, A., and Rossi, S. (2014). Sovereign default, domestic banks, and financial institutions. *The Journal of Finance*, 69(2):819–866.

Gertler, M. and Kiyotaki, N. (2015). Banking, liquidity, and bank runs in an infinite horizon economy. *American Economic Review*, 105(7):2011–43.

Gorton, G. and Ordonez, G. (2014). Collateral crises. *American Economic Review*, 104(2):343–78.

Gorton, G. and Ordonez, G. (2020). Good booms, bad booms. *Journal of the European Economic Association*, 18(2):618–665.

Graham, J. R., Leary, M. T., and Roberts, M. R. (2015). A century of capital structure: The leveraging of corporate america. *Journal of Financial Economics*, 118(3):658–683.

Gustafson, M. T., Ivanov, I. T., and Meisenzahl, R. R. (2021). Bank monitoring: Evidence from syndicated loans. *Journal of Financial Economics*, 139(2):452–477.

Holmström, B. and Tirole, J. (1998). Private and public supply of liquidity. *Journal of Political Economy*, 106(1):1–40.

Ivashina, V. (2009). Asymmetric information effects on loan spreads. *Journal of Financial Economics*, 92(2):300–319.

Ivashina, V. and Sun, Z. (2011). Institutional stock trading on loan market information. *Journal of Financial Economics*, 100(2):284–303.

Ivashina, V. and Vallee, B. (2020). Weak credit covenants. Technical report, National Bureau of Economic Research.

Keys, B. J., Mukherjee, T., Seru, A., and Vig, V. (2010). Did securitization lead to lax screening? evidence from subprime loans. *The Quarterly Journal of Economics*, 125(1):307–362.

Kilian, L. and Vigfusson, R. J. (2017). The role of oil price shocks in causing us recessions. *Journal of Money, Credit and Banking*, 49(8):1747–1776.

Lisowsky, P., Minnis, M., and Sutherland, A. (2017). Economic growth and financial statement verification. *Journal of Accounting Research*, 55(4):745–794.

Ruckes, M. (2004). Bank competition and credit standards. *The Review of Financial Studies*, 17(4):1073–1102.

Sufi, A. (2007). Information asymmetry and financing arrangements: Evidence from syndicated loans. *The Journal of Finance*, 62(2):629–668.

APPENDIX

Contracts

We can use r_L^{b*} to rewrite the bargaining problem between the bank and the late agent as

$$\max_{0\leq r_L^g \leq 2e-(\omega+c)+x-\frac{e-c}{\lambda}} \left\{ \lambda^\theta \left[2e-(\omega+c)+x-\frac{e-c}{\lambda}-r_L^g \right]^\theta \left[\lambda r_L^g + (1-\lambda) r_L^{b*} - e \right]^{1-\theta} \right\}. \quad (.1)$$

In what follows, we show that it is optimal to choose an interior solution to r_L^g. If we let ν_0 denote the Lagrange multiplier associated with the lower bound of r_L^g, and ν_1 denote the Lagrange multiplier associated with the upper bound of r_L^g, the first-order condition of (.1) is

$$\frac{(1-\theta)\lambda}{\lambda r_L^g + (1-\lambda)\left[2e-(\omega+c)+s(\mu_B,\mu_L)\right]-e} - \frac{\theta}{2e-(\omega+c)+x-\frac{e-c}{\lambda}-r_L^g} = \nu_1 - \nu_0.$$

To rule out $r_L^g = 0$, we need

$$e+s(\mu_B,\mu_L) \leq \omega + c + \frac{\lambda}{1-\lambda}\left\{ e + \frac{1-\theta}{\theta}\left[2e-(\omega+c)+x-\frac{e-c}{\lambda} \right] \right\}.$$

In turn, to rule out $r_L^g = 2e-(\omega+c)+x-\frac{e-c}{\lambda}$, we need

$$\frac{(1-\theta)\lambda}{\lambda r_L^g + (1-\lambda)\left[2e-(\omega+c)+s(\mu_B,\mu_L)\right]-e} \leq \frac{\theta}{2e-(\omega+c)+x-\frac{e-c}{\lambda}-r_L^g}.$$

Since the left-hand side evaluated at $r_L^g = 2e-(\omega+c)+x-\frac{e-c}{\lambda}$ is equal to infinite, this inequality is always satisfied. As a result, r_L^g is an interior solution, given by

$$r_L^{g*} = 2e-(\omega+c)+x-\frac{e-c}{\lambda}-\theta\left[\frac{\lambda x - \omega}{\lambda} + \frac{1-\lambda}{\lambda} s(\mu_B,\mu_L) \right].$$

Proof of Proposition 1 In the main text, we showed that $\mu_B = \mu_B^*$ for all $z \leq G_\gamma(\mu_B^*)$. In what follows, we characterize the bank's monitoring choice when $z > G_\gamma(\mu_B^*)$. First, we examine the region of parameters where $G_\gamma(\mu_B^*) \geq G_\gamma(0)$, which can be rewritten as

$$\gamma \leq \gamma' \equiv \frac{1+\theta(1-\lambda)s\left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{1+\alpha}{1-\alpha}}}{\alpha(1-\theta)} = \frac{1+\mu_L^*}{\alpha(1-\theta)}.$$

In this case, for all $z > G_\gamma(\mu_B^*)$, we have $z > G_\gamma(0)$. Since $G_\gamma''(\mu_B) > 0$, we must have $\mu_B^- < 0$. The bank can then either choose μ_B^+ or it can choose zero monitoring. The latter choice is dominated if and only if $\mu_B^+ \leq 2\mu_B^*$. This is so because $\Pi_B(\mu_B) \geq 0$ if and only if $\mu_B \leq 2\mu_B^*$. Since $G_\gamma(\mu_B^*) \geq G_\gamma(0)$ and $G_\gamma''(\mu_B) > 0$, $G_\gamma(\mu_B)$ is strictly increasing in μ_B, for all $\mu_B \geq \mu_B^*$, which implies that $\mu_B^+(z) = G_\gamma^{-1}(z)$ is well defined and increases continuously in $z > G_\gamma(\mu_B^*)$. As a result, $\Pi_B\left(\mu_B^+(z)\right) \geq 0$ for all $z \in (G_\gamma(\mu_B^*), G_\gamma(2\mu_B^*)]$, and the bank chooses μ_B^+; while $\Pi_B\left(\mu_B^+\right) < 0$ for all $z > G_\gamma(2\mu_B^*)$, and the bank chooses zero monitoring.

Second, we examine the region of parameters where $G_\gamma(\mu_B^*) < G_\gamma(0)$, i.e.,

$$\gamma > \gamma' \equiv \frac{1 + \theta(1-\lambda)s\left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{1+\alpha}{1-\alpha}}}{\alpha(1-\theta)} = \frac{1+\mu_L^*}{\alpha(1-\theta)}.$$

We start by examining the scenario where $G_\gamma(\mu_B^*) < G_\gamma(0) < z$. In this case, $G_\gamma''(\mu_B) > 0$ implies that $\mu_B^- < 0$. As in the previous scenario, the bank then either chooses μ_B^+ or it chooses zero monitoring. The latter choice is optimal if $\Pi_B\left(\mu_B^+\right) < 0$, which occurs for all $z > G_\gamma(0)$ if and only if $G_\gamma(0) \geq G_\gamma(2\mu_B^*)$, which can be rewritten as

$$\gamma \geq \underline{\gamma} \equiv \frac{1 + 2\theta(1-\lambda)s\left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{1+\alpha}{1-\alpha}}}{\alpha(1-\theta)} = \frac{1+2\mu_L^*}{\alpha(1-\theta)}.$$

Thus, if $\gamma \geq \underline{\gamma}$ and $z > G_\gamma(0)$, the bank chooses zero monitoring. If, instead $\gamma \in \left(\gamma', \underline{\gamma}\right)$ and $z > G_\gamma(0)$, the bank chooses μ_B^+ for all $z \in [G_\gamma(0), G_\gamma(2\mu_B^*)]$, and it chooses zero monitoring for all $z > G_\gamma(2\mu_B^*)$.

Finally, we examine the region where $G_\gamma(\mu_B^*) < z < G_\gamma(0)$. Since $G_\gamma(\mu_B^*) < G_\gamma(0)$, $G_\gamma''(\mu_B) > 0$ implies that, for all $z \in (G_\gamma(\mu_B^*), G_\gamma(0))$, $\mu_B^-(z) = G_\gamma^{-1}(z)$ is well defined and decreases continuously in $z > G_\gamma(\mu_B^*)$. Since $\mu_B^-(z)$ is now a feasible choice, the bank prefers $\mu_B^+(z)$ if and only if $\Pi_B\left(\mu_B^+(z)\right) \geq \Pi_B\left(\mu_B^-(z)\right)$, which can be rewritten as

$$\mu_B^+(z) + \mu_B^-(z) \leq 2\theta(1-\lambda)s\left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{\alpha}{1-\alpha}}. \tag{.2}$$

To find $\mu_B^+(z) + \mu_B^-(z)$, we solve $z = G_\gamma(\widehat{\mu}_B)$, which gives

$$\widehat{\mu}_B(z) = \frac{\left[z - \frac{1}{(1-\theta)(1-\lambda)\alpha}\right] v^{\frac{1}{1-\alpha}} \frac{1-\lambda}{\gamma} \pm \left\{\left(z - \frac{s}{v}\right)^2 v^{\frac{2}{1-\alpha}} - 4\frac{1-\lambda}{\gamma} s v^{\frac{1+\alpha}{1-\alpha}} \left[1 - z\frac{1-\lambda}{\gamma}\right]\right\}}{2\frac{1-\lambda}{\gamma} s v^{\frac{1+\alpha}{1-\alpha}}},$$

where

$$v = [(1-\theta)(1-\lambda)s\alpha].$$

This implies

$$\mu_B^+(z) + \mu_B^-(z) = \frac{z - \frac{1}{(1-\theta)(1-\lambda)\alpha}}{s\,[(1-\theta)(1-\lambda)s\alpha]^{\frac{\alpha}{1-\alpha}}}.$$

We can then rewrite (.2) as

$$z \leq \frac{1 + 2\theta(1-\lambda)s\,[(1-\theta)(1-\lambda)s\alpha]^{\frac{1+\alpha}{1-\alpha}}}{(1-\theta)(1-\lambda)\alpha} = \frac{\underline{\gamma}}{1-\lambda}.$$

Since $z < G_\gamma(0)$, we obtain that, if $\gamma < \underline{\gamma}$, then $G_\gamma(0) < \frac{\underline{\gamma}}{1-\lambda}$ and we have $z \leq \frac{\underline{\gamma}}{1-\lambda}$ for all $z \in (G_\gamma(\mu_B^*), G_\gamma(0))$. This implies that if $\gamma < \underline{\gamma}$, the bank chooses $\mu_B^+(z)$ for all $z \in (G_\gamma(\mu_B^*), G_\gamma(0))$. In turn, since $z > G_\gamma(\mu_B^*)$, if $\frac{\underline{\gamma}}{1-\lambda} < G_\gamma(\mu_B^*)$, the bank chooses $\mu_B^-(z)$ for all $z \in (G_\gamma(\mu_B^*), G_\gamma(0))$. We can rewrite $\frac{\underline{\gamma}}{1-\lambda} < G_\gamma(\mu_B^*)$ as

$$\gamma > \overline{\gamma} = \underline{\gamma} + \frac{\mu_L^{*2}}{(1-\theta)\alpha}.$$

Lastly, if $\gamma \in (\underline{\gamma}, \overline{\gamma})$ and $z \in (G_\gamma(\mu_B^*), G_\gamma(0))$, the bank chooses $\mu_B^+(z)$ if $z \leq \frac{\underline{\gamma}}{1-\lambda}$ and it chooses $\mu_B^-(z)$ otherwise.

Details on Welfare Characterization

We are interested in describing how welfare changes when we move from the region where the information constraint does not bind to the ones where it binds. In order to do so, we characterize the welfare evolves as a function of z and γ. As before, this allows to examine how the changes in monitoring described in proposition 1 impact welfare in a scenario where all parameters that directly affect the welfare are kept constant.

In particular, if $\gamma > \overline{\gamma}$ and the bank chooses $\mu_B^-(z)$ in the interval $\left(G_\gamma(\mu_B^*), \frac{\underline{\gamma}}{1-\lambda}\right]$, we obtain that welfare is constant for all $z \leq G_\gamma(\mu_B^*)$, it is strictly decreasing in the interval $\left(G_\gamma(\mu_B^*), \frac{\underline{\gamma}}{1-\lambda}\right]$, and it converges to λx for all $z \geq \frac{\underline{\gamma}}{1-\lambda}$.

A distinct scenario takes place if the bank chooses $\mu_B^+(z)$. Let us first consider the region where $\gamma \leq \underline{\gamma}$. In this region, since $\mu_B^{\mathcal{W}} < 2\mu_B^*$, there exists $\mu_B^+(z) = G_\gamma^{-1}(z)$ such that $\mu_B^+(z) = \mu_B^{\mathcal{W}}$. As a function of γ the value of z that implements the welfare optimal monitoring satisfies $z = G_\gamma\left(\mu_B^{\mathcal{W}}\right)$. The results in Proposition 1 then implies that, for all $\gamma \leq \underline{\gamma}$, welfare evolves as follows. It is constant for all $z \leq G_\gamma(\mu_B^*)$, it becomes strictly increasing in the interval $\left(G_\gamma(\mu_B^*), G_\gamma\left(\mu_B^{\mathcal{W}}\right)\right]$, achieving the welfare maximizing level at $z = G_\gamma\left(\mu_B^{\mathcal{W}}\right)$; it is then strictly decreasing in the interval $\left(G_\gamma\left(\mu_B^{\mathcal{W}}\right), G_\gamma(2\mu_B^*)\right]$, converging to the constant level λx in the interval $z > G_\gamma(2\mu_B^*)$.

Let us now consider the region where $\gamma \in \left(\underline{\gamma}, \overline{\gamma}\right)$. In this case, the largest value that $\mu_B^+(z)$ achieves is given by $\mu_B^+(\frac{\gamma}{1-\lambda})$. We obtain that $\mu_B^+(\frac{\gamma}{1-\lambda}) > \mu_B^{\mathcal{W}}$ if and only if $\frac{\gamma}{1-\lambda} > G\left(\mu_B^{\mathcal{W}}\right)$, which can be rewritten as

$$\gamma \leq \gamma^+ \equiv \frac{\left[1 + \frac{\theta-(1-\theta)(1-\alpha)}{\theta}\mu_L^*\right]\left[1 + \frac{1-(1-\theta)\alpha}{\theta}\mu_L^*\right]}{(1-\theta)\alpha}.$$

Since $\gamma^+ < \overline{\gamma}$, we obtain that $\frac{\gamma}{1-\lambda} > G\left(\mu_B^{\mathcal{W}}\right)$ and $\mu_B^+(\frac{\gamma}{1-\lambda}) > \mu_B^{\mathcal{W}}$. This implies that the welfare maximizing level of monitoring is also achieved when $\gamma \in \left(\underline{\gamma}, \overline{\gamma}\right)$ and $z \in \left(G_\gamma(\mu_B^*), \frac{\gamma}{1-\lambda}\right]$. Now, a distinct feature of this region is that, unlike in the case where $\gamma \notin \left(\underline{\gamma}, \overline{\gamma}\right)$, there is a transition from over monitoring to under monitoring. This transition introduces a discontinuity of the bank's monitoring at $z = \frac{\gamma}{1-\lambda}$, which translates into a discrete welfare reduction. Precisely, welfare evolves as follows. It is constant for all $z \leq G_\gamma(\mu_B^*)$, it is strictly increasing in the interval $\left(G_\gamma(\mu_B^*), G\left(\mu_B^{\mathcal{W}}\right)\right]$, and it is strictly decreasing in the interval $\left(G\left(\mu_B^{\mathcal{W}}\right), \frac{\gamma}{1-\lambda}\right]$. At $z = \frac{\gamma}{1-\lambda}$, there is a discrete reduction as the bank moves from over monitoring into under monitoring. Welfare then decreases in the interval $\left(\frac{\gamma}{1-\lambda}, \frac{\gamma}{1-\lambda}\right]$ and it converges to λx for all $z > \frac{\gamma}{1-\lambda}$.

Consider next the impact of γ. For example, in the region of parameters where the information constraint binds and the bank chooses μ_B^+, we can rewrite rewrite $z = G_\gamma(\mu_B^+)$ as

$$z(1-\lambda) = \frac{\mu_L^+}{\alpha(1-\theta)} + \frac{\gamma}{\mu_L^+ + 1}.$$

We obtain

$$\epsilon_{\mu_L^+,\gamma} = -\frac{\frac{1}{\mu_L^+ + 1}\frac{\gamma}{1-\lambda}}{z - \frac{2\widehat{\mu}_L + 1}{\left(\mu_L^+ + 1\right)^2}\frac{\gamma}{1-\lambda}},$$

where we use (2.4) to recover μ_B^+. In the Appendix we show that $z > \frac{2\mu_L^+ + 1}{\left(\mu_L^+ + 1\right)^2}\frac{\gamma}{1-\lambda}$. Since $z > G_\gamma(\mu_B^*)$ in the region of parameters where the bank cannot chose μ_B^*, if $G_\gamma(\mu_B^*) > \frac{2\mu_L^+ + 1}{\left(\mu_L^+ + 1\right)^2}\frac{\gamma}{1-\lambda}$, then $\epsilon_{\widehat{\mu}_L,\gamma} > 0$. Since $\mu_L^+ > \mu_L^*$, a sufficient condition for the latter inequality to hold is $G_\gamma(\mu_B^*) > \frac{2\mu_L^* + 1}{\left(\mu_L^* + 1\right)^2}\frac{\gamma}{1-\lambda}$, which can be rewritten as $\gamma < \overline{\gamma}$, and is always true in the region where the bank chooses μ_L^+.

This implies that $\epsilon_{\mu_L^+,\gamma} < 0$, i.e., an increase in γ reduces the monitoring of the bank. In the region of parameters where $z \in \left(G_\gamma\left(\mu_B^*\right), G_\gamma\left(\mu_B^{\mathcal{W}}\right)\right)$, this reduction in monitoring necessarily causes a reduction in the welfare. Thus, an exogenous increase in the cost of acquiring information about the project may actually hurt welfare, even though it potentially contributes to the opacity of the project.

Data

In the main text we described the main cleaning of our matched data. In what follows we detail a number of other more technical adjustments. First of all, we focus on the package level instead of the facility level. Focus on a facility-loan level would generate a selection bias in the numbers of repeated interactions because we would sum the same bank members over multiple loan facilities within a loan package. Further, we exclude loan packages to financial firms and utilities (public services). Finally, in the same line of Graham et al. (2015), we exclude loans that are likely to be amendments to existing loans. DealScan misreports these loans as new loans though they do not involve new money.

Tables & Figures

Figure 1 Aggregate US Syndicated Loans Outstanding

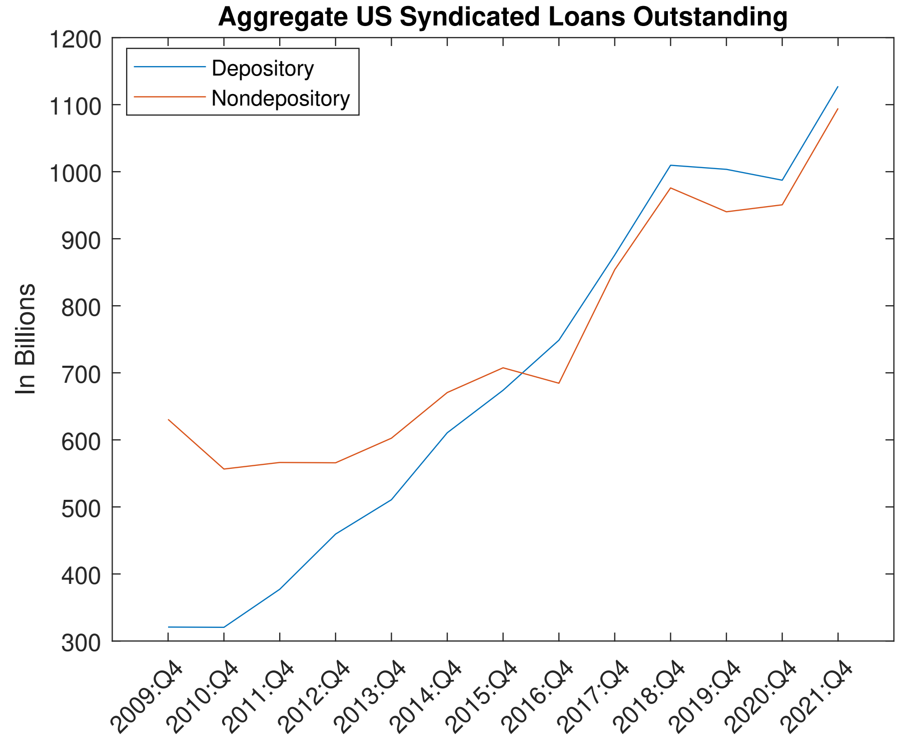


Figure 2 Number of US Commercial Banks

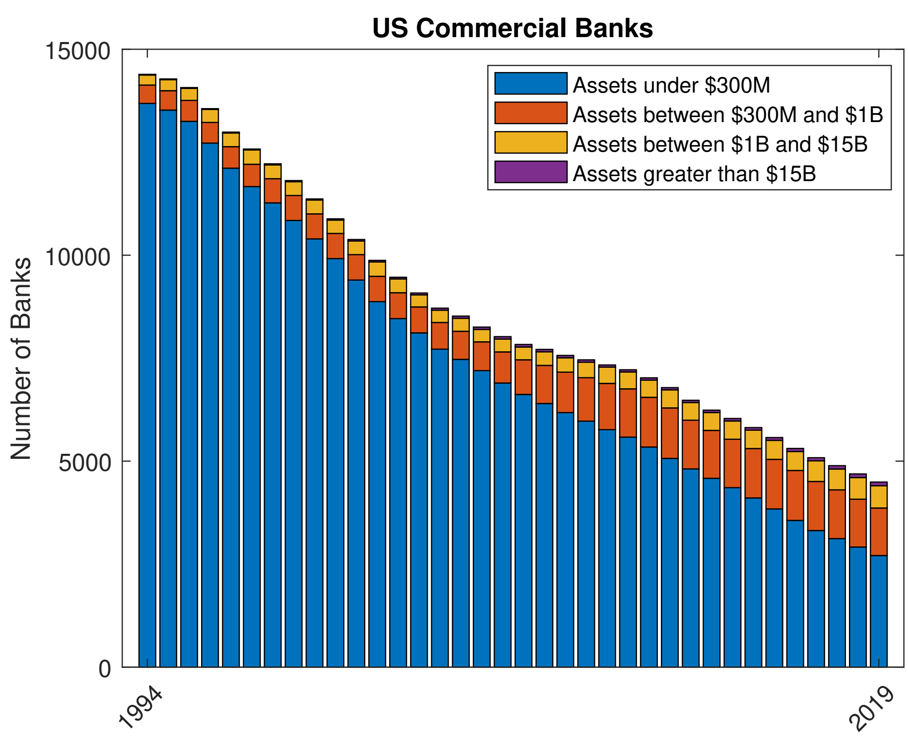


Figure 3 Relationship between Liquidity and Investment Complexity

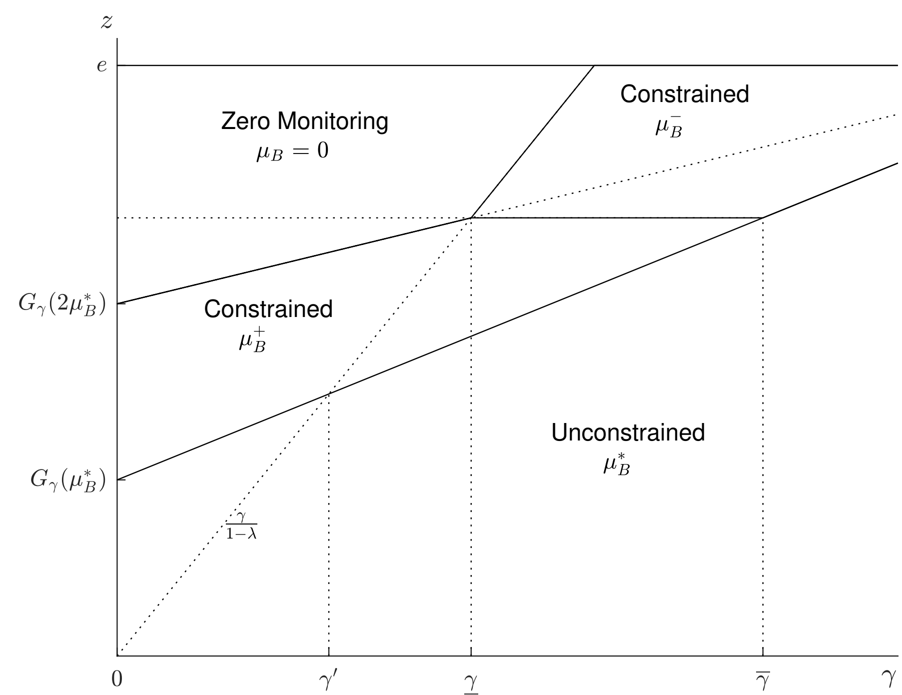
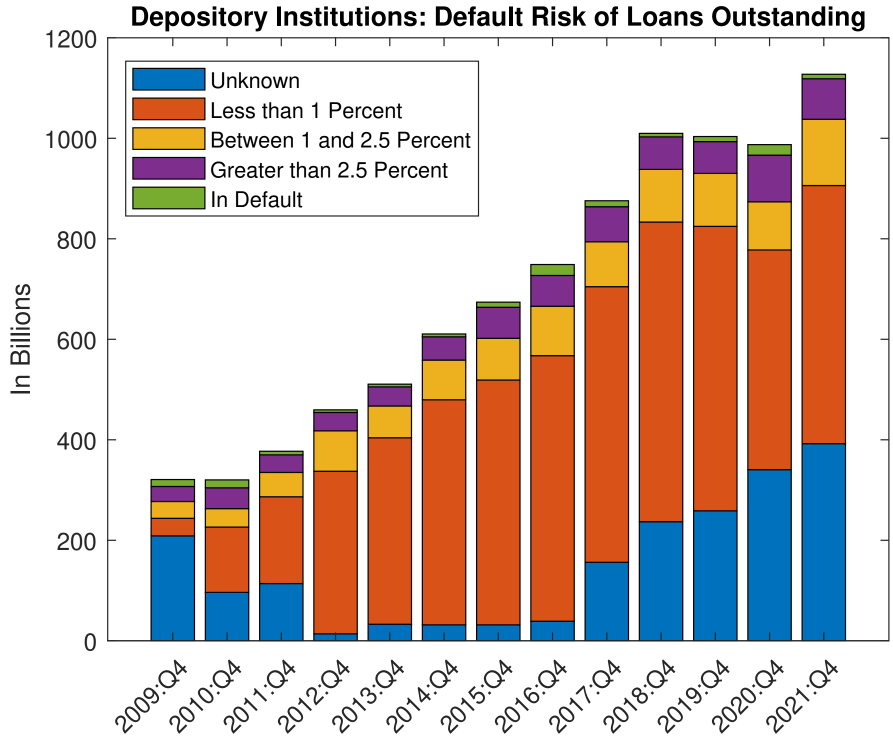


Figure 4 Portfolio Risks of US Syndicated Loans



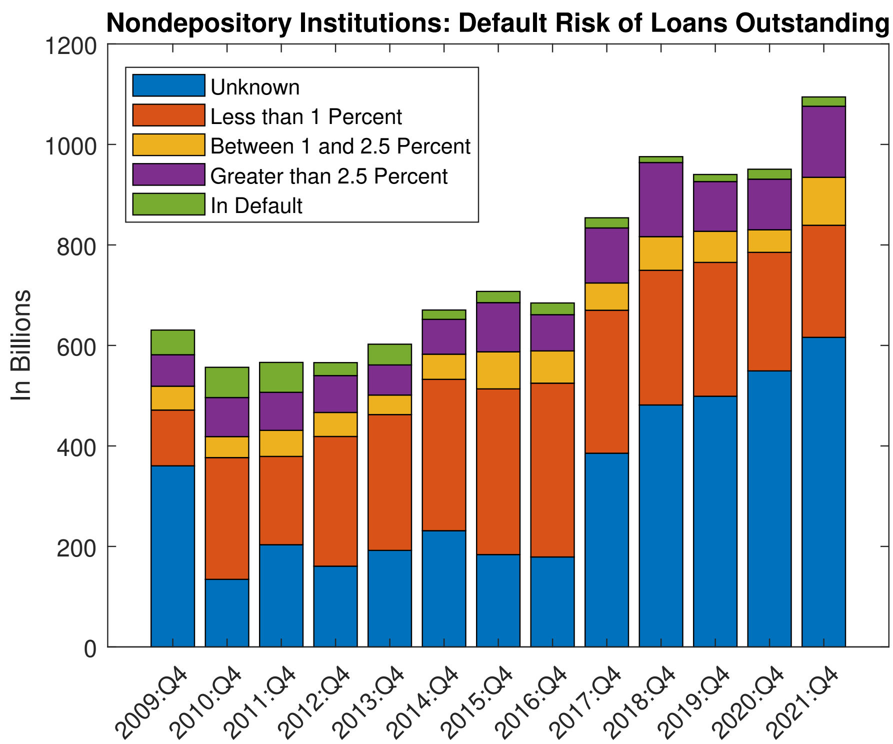


Figure 5 Undermonitoring in Constrained Region

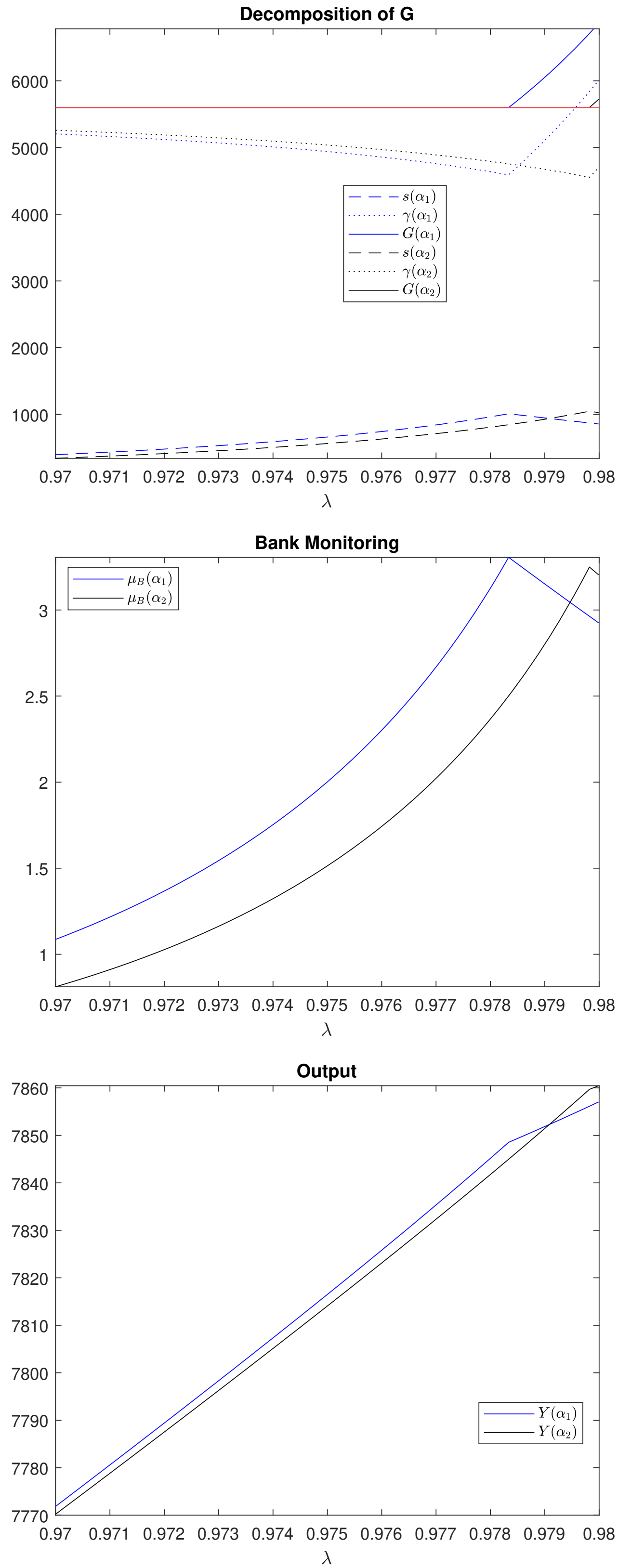


Figure 6 Overmonitoring in Constrained Region

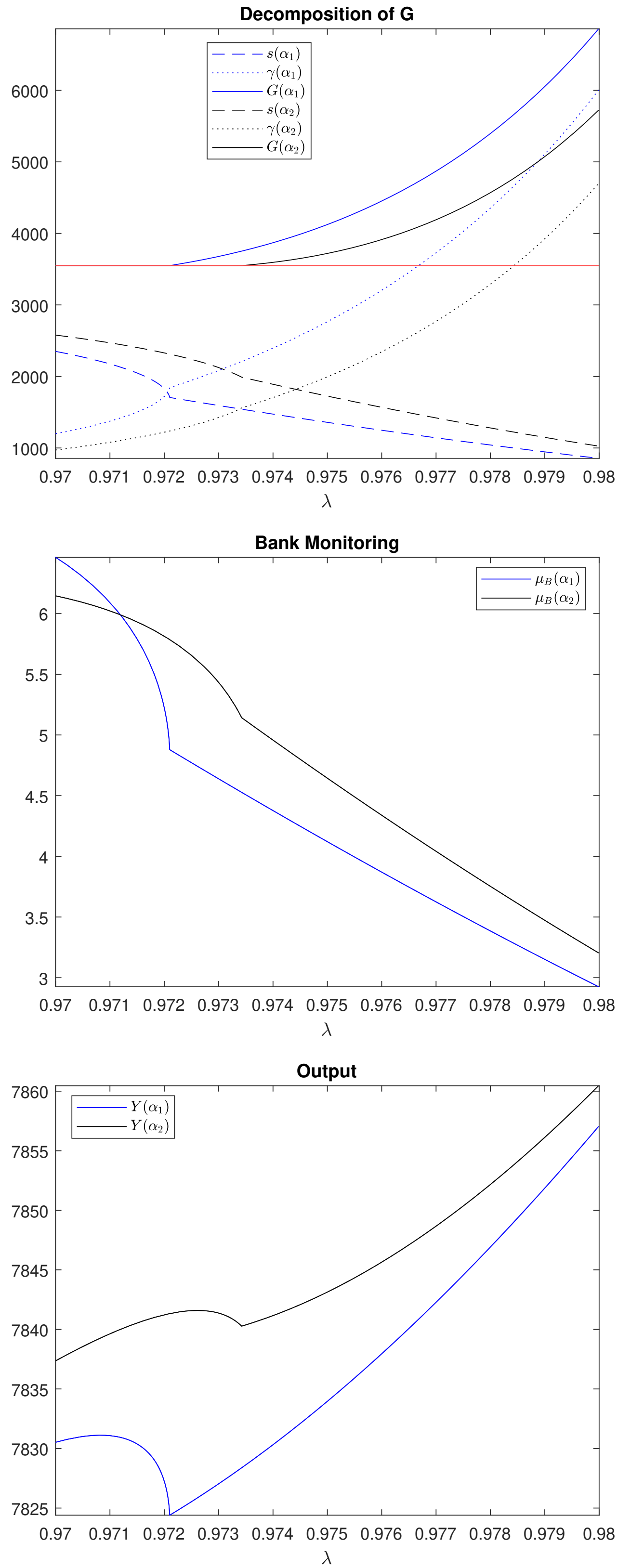
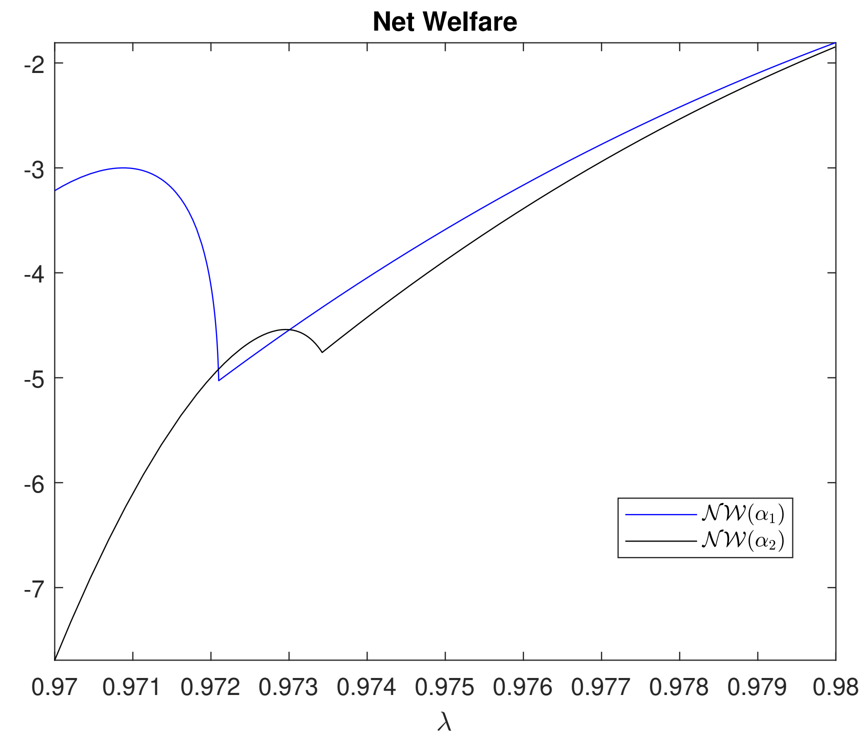


Figure 7 Welfare Implications



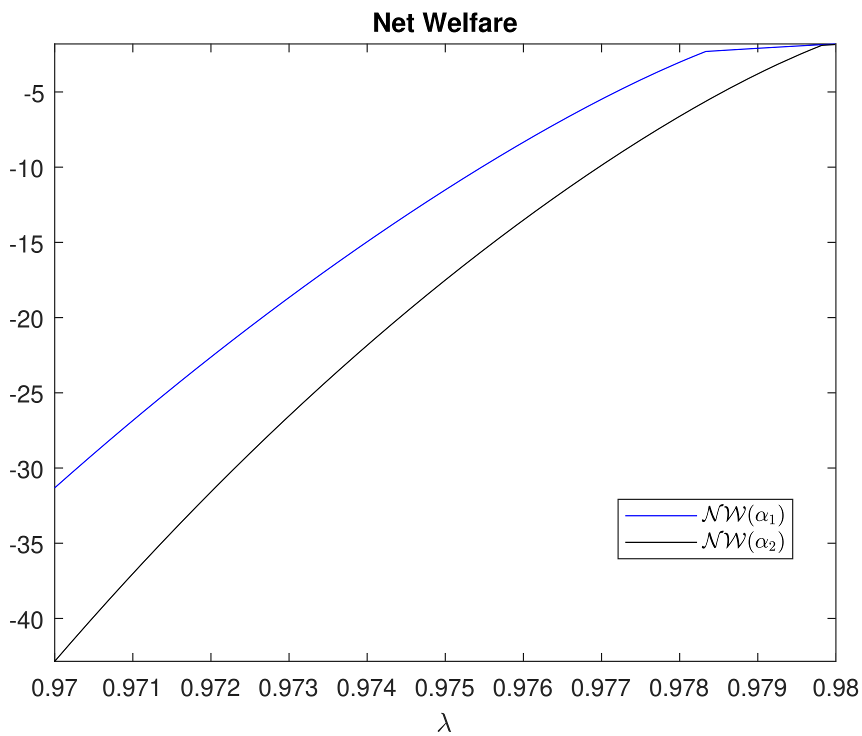
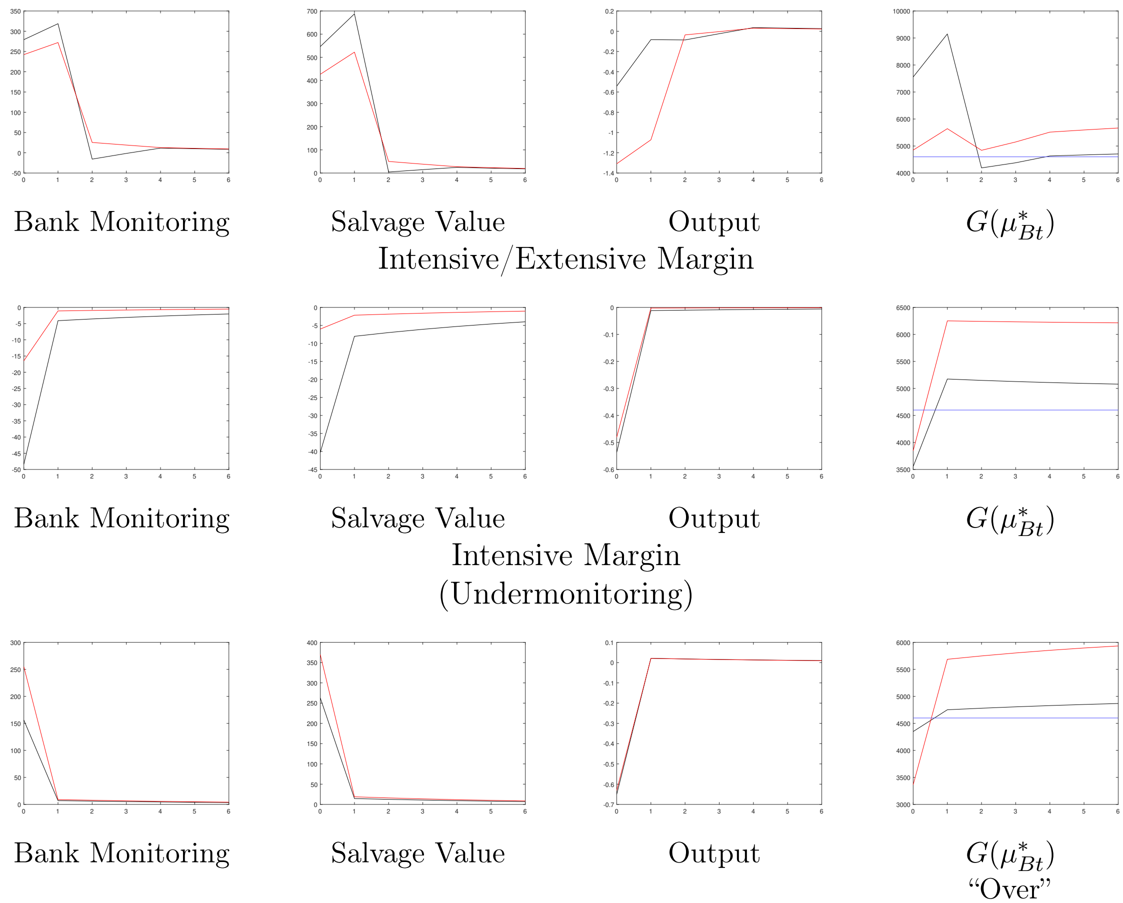


Figure 8 Responses to Recessionary Shock in Dynamic Economies



Intensive Margin
(Overmonitoring)
α_1=Red, α_2=Black

Figure 9 Monitoring and Oil Shocks

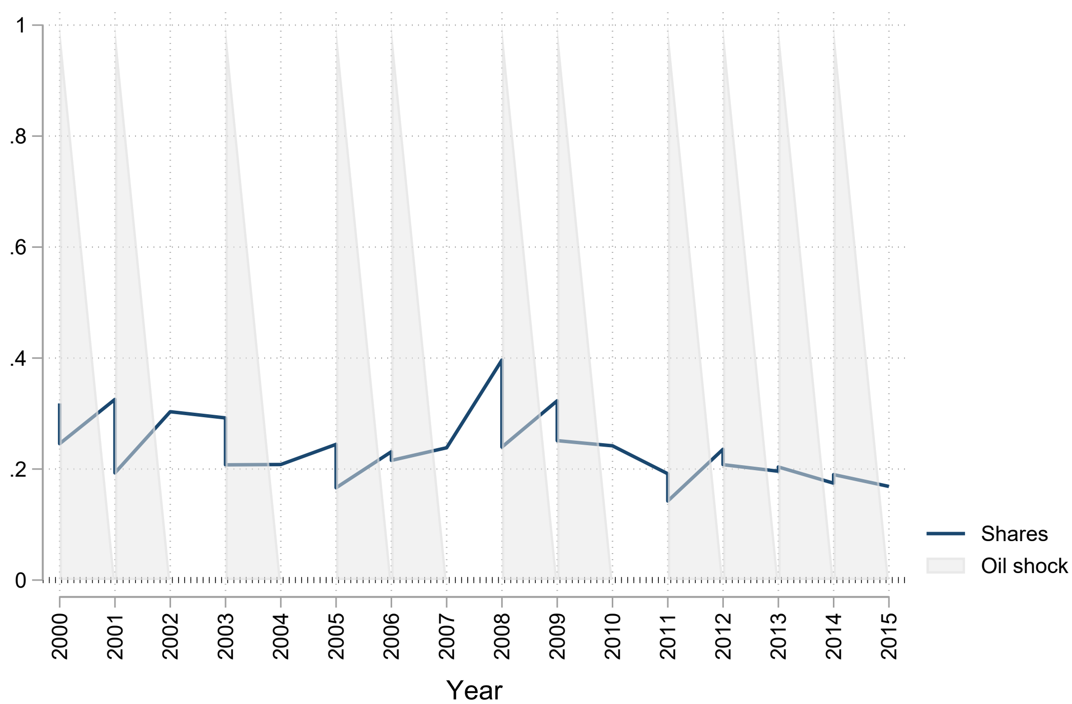


Table 1 Summary Statistics

	I	II	III	IV	V	VI
	N	Mean	sd	p25	p50	p75
Firm asset growth	129,620	-0.064	0.203	-0.092	-0.027	0.014
Firm fixed asset growth	128,640	-0.059	0.236	-0.087	-0.024	0.015
1-HHI	129,620	0.962	0.059	0.959	0.984	0.993
Past interactions	129,620	0.012	0.060	0.000	0.000	0.000
Oil shock	129,620	0.115	0.320	0.000	0.000	0.000
GFC	129,620	0.078	0.268	0.000	0.000	0.000
Maturity (month)	129,620	47.516	22.882	35.000	60.000	60.000
AISD (bps)	129,620	158.178	112.650	65.000	150.000	225.000
Refinance	129,620	0.358	0.158	0.000	0.000	1.000
Firm's leverage	129,620	0.320	0.226	0.180	0.292	0.420
ROA	129,620	0.033	0.596	0.009	0.035	0.064

Table 2 Firms' Resilience to Aggregate Shocks (Asset Growth)

Dependent variable:	Firm Asset Growth							
Group:	Past bank-to-bank interactions				1-HHI			
	I	II	III	IV	V	VI	VII	VIII
Banking complexity	0.020*	0.028**	0.020*	0.029**	0.103***	0.113***	0.093***	0.097***
	(1.768)	(2.559)	(1.664)	(2.517)	(5.348)	(5.133)	(5.038)	(4.745)
Oil shock	0.005***		0.005***		-0.061***		-0.063***	
	(5.147)		(5.239)		(-3.910)		(-3.938)	
Banking complexity * Oil shock	0.025**		0.025*		0.069***		0.072***	
	(2.192)		(1.883)		(4.339)		(4.366)	
Banking complexity * GFC		-0.057**		-0.065**		-0.121***		-0.107***
		(-2.245)		(-2.292)		(-4.284)		(-3.702)
Loan controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	129,620	136,324	128,563	135,141	129,620	136,324	128,563	135,141
Adjusted R-squared	0.353	0.347	0.367	0.361	0.354	0.348	0.367	0.362
Purpose FE	Y	Y	Y	Y	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y			Y	Y		
Bank FE	Y	Y			Y	Y		
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Bank*Time FE			Y	Y			Y	Y
Clustered standard errors	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Table 3 Firms' Resilience to Aggregate Shocks (Fixed Asset Growth)

Dependent variable:	Firm Fixed Asset Growth							
Group:	Past bank-to-bank interactions				1-HHI			
	I	II	III	IV	V	VI	VII	VIII
Banking complexity	0.041***	0.044***	0.043***	0.046***	0.105***	0.118***	0.094***	0.102***
	(4.326)	(4.111)	(4.488)	(4.252)	(4.912)	(5.075)	(4.572)	(4.583)
Oil shock	0.005***		0.005***		-0.058***		-0.061***	
	(3.229)		(3.095)		(-3.016)		(-2.955)	
Banking complexity * Oil shock	0.027**		0.033**		0.065***		0.069***	
	(2.154)		(2.156)		(3.338)		(3.255)	
Banking complexity * GFC		-0.088***		-0.083**		-0.198***		-0.181***
		(-3.629)		(-2.095)		(-5.254)		(-4.717)
Loan controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	128,637	135,223	127,578	134,038	128,637	135,223	127,578	134,038
Adjusted R-squared	0.352	0.346	0.366	0.361	0.353	0.346	0.366	0.361
Purpose FE	Y	Y	Y	Y	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y			Y	Y		
Bank FE	Y	Y			Y	Y		
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Bank*Time FE			Y	Y			Y	Y
Clustered standard errors	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Table 4 Instrumental variables estimation

	I	II	III	IV
Panel A: First-stage results				
Dependent variable:	Banking complexity			
Group:	Past interactions		1-HHI	
Acquired banking complexity	0.217***	0.217***	0.001***	0.001***
	(3.038)	(3.038)	(3.424)	(3.424)
Panel B: Second-stage results				
Dependent variable:	Firm Asset Growth			
Banking complexity	0.063*	0.075***	2.139	1.397
	(1.684)	(3.645)	(0.835)	(0.710)
Oil shock	0.005***		-0.457***	
	(5.252)		(-4.630)	
Banking complexity * Oil shock	0.056*		0.482***	
	(1.769)		(4.695)	
Banking complexity * GFC		-0.619***		-0.747**
		(-3.404)		(-2.475)
Loan controls	Y	Y	Y	Y
Firm controls	Y	Y	Y	Y
Observations	128,563	132,826	128,563	135,141
Adjusted R-squared	0.367	0.430	0.367	0.361
F-stat	3.021	3.021	14.9	14.9
Purpose FE	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Bank*Time FE	Y	Y	Y	Y
Clustered standard errors	Bank	Bank	Bank	Bank

Table 5 Investment Complexity (Past Interaction)

Dependent variable:	Firm Asset Growth				Firm Fixed Asset Growth			
Investment complexity:	*High complex*	*Low complex*	*High complex*	*Low complex*	*High complex*	*Low complex*	*High complex*	*Low complex*
	I	II	III	IV	V	VI	VII	VIII
Past interactions	0.056	0.040**	0.052	0.050**	0.071***	-0.021	0.080***	-0.029
	(0.925)	(2.374)	(0.995)	(2.548)	(4.835)	(-0.419)	(4.719)	(-0.612)
Past interactions * GFC	-0.144	-0.047**	-0.201	-0.065**	-0.149***	-0.042	-0.175***	0.105
	(-1.109)	(-2.320)	(-1.108)	(-2.247)	(-4.918)	(-0.227)	(-4.894)	(0.486)
Loan controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	57,470	75,651	57,324	74,685	56,935	75,131	56,787	74,173
Adjusted R-squared	0.468	0.380	0.488	0.388	0.369	0.447	0.370	0.471
Purpose FE	Y	Y	Y	Y	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y			Y	Y		
Bank FE	Y	Y			Y	Y		
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Bank*Time FE			Y	Y			Y	Y
Clustered standard errors	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Table 6 Investment Complexity (HHI)

Dependent variable:	Firm Asset Growth				Firm Fixed Asset Growth			
Investment complexity:	*High complex*	*Low complex*	*High complex*	*Low complex*	*High complex*	*Low complex*	*High complex*	*Low complex*
	I	II	III	IV	V	VI	VII	VIII
1-HHI	0.156***	0.041*	0.138***	0.041*	0.134***	0.069***	0.116***	0.065***
	(4.460)	(1.700)	(4.100)	(1.686)	(3.698)	(3.222)	(3.180)	(3.114)
1-HHI * GFC	-0.169***	-0.081**	-0.146**	-0.080**	-0.216**	-0.164***	-0.188**	-0.161***
	(-2.798)	(-2.333)	(-2.482)	(-2.191)	(-2.396)	(-4.896)	(-1.978)	(-4.839)
Loan controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	58,505	76,933	58,362	75,966	57,951	76,385	57,806	75,424
Adjusted R-squared	0.396	0.324	0.416	0.330	0.392	0.312	0.410	0.319
Purpose FE	Y	Y	Y	Y	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y			Y	Y		
Bank FE	Y	Y			Y	Y		
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Bank*Time FE			Y	Y			Y	Y
Clustered standard errors	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Table 7 Firm profitability

	I	II	III	IV
Dependent variable:	Firm Asset Growth		Firm Fixed Asset Growth	
Profitability group:	Below	Below	Below	Below
Panel A: Past bank-to-bank interactions				
Past interactions	0.018	0.022	0.045***	0.053***
	(1.252)	(1.473)	(3.250)	(3.199)
Oil shock	0.011***		0.009***	
	(6.056)		(5.185)	
Past interactions * Oil shock	0.042*		0.055*	
	(1.743)		(1.755)	
Past interactions * GFC		0.050		-0.089*
		(1.088)		(-1.935)
Observations	63,889	67,562	63,371	66,938
Adjusted R-squared	0.472	0.477	0.449	0.445
Panel B: 1-HHI				
1-HHI	0.052**	0.055**	0.086***	0.089***
	(2.213)	(2.061)	(3.368)	(3.195)
Oil shock	-0.071***		-0.074**	
	(-3.343)		(-2.421)	
1-HHI * Oil shock	0.086***		0.088***	
	(3.913)		(2.794)	
1-HHI * GFC		-0.022		-0.158***
		(-0.616)		(-3.785)
Observations	63,889	67,562	63,371	66,938
Adjusted R-squared	0.472	0.477	0.449	0.445
Purpose FE	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Clustered standard errors	Bank	Bank	Bank	Bank

Table 8 Firm Level Evidence (Asset Growth)

Dependent variable:	Firm Asset Growth					
	Post: 1 year		*Post: 2 years*		*Post: 3 years*	
	I	II	III	IV	V	VI
Panel A: Past bank-to-bank interactions						
Past interactions	0.075**	0.117***	0.155***	0.238***	0.198**	0.318***
	(2.071)	(3.138)	(2.738)	(3.900)	(2.252)	(3.189)
Oil shock	0.000		-0.005		-0.005	
	(0.193)		(-1.592)		(-1.053)	
Past interactions * Oil shock	0.019		0.102*		0.116	
	(0.585)		(1.830)		(1.483)	
Past interactions * GFC		-0.256		-0.600***		-0.754***
		(-1.603)		(-3.209)		(-3.126)
Observations	23,142	24,280	22,782	23,904	21,288	22,367
Adjusted R-squared	0.175	0.172	0.240	0.235	0.284	0.284
Panel B: 1-HHI						
1-HHI	0.078***	0.092***	0.185***	0.207***	0.375***	0.433***
	(3.028)	(3.499)	(4.879)	(5.302)	(6.567)	(7.182)
Oil shock	-0.005		-0.004		-0.020	
	(-0.243)		(-0.129)		(-0.438)	
1-HHI * Oil shock	0.007		0.000		0.019	
	(0.286)		(0.014)		(0.390)	
1-HHI * GFC		-0.095*		-0.171**		-0.217*
		(-1.836)		(-2.406)		(-1.885)
Observations	23,142	24,280	22,782	23,904	21,288	22,367
Adjusted R-squared	0.175	0.172	0.241	0.237	0.287	0.287
Time FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Clustered standard errors	Firm	Firm	Firm	Firm	Firm	Firm

Table 9 Firm level evidence (Fixed Asset Growth)

Dependent variable:	Firm Fixed Asset Growth					
	Post: 1 year		*Post: 2 years*		*Post: 3 years*	
	I	II	III	IV	V	VI
Panel A: Past bank-to-bank interactions						
Past interactions	0.092**	0.119***	0.196***	0.259***	0.214**	0.313***
	(2.051)	(2.614)	(3.130)	(4.063)	(2.238)	(3.061)
Oil shock	-0.001		-0.006		-0.010*	
	(-0.477)		(-1.586)		(-1.902)	
Past interactions * Oil shock	0.052		0.098*		0.121	
	(1.423)		(1.806)		(1.522)	
Past interactions * GFC		-0.320**		-0.686***		-0.967***
		(-2.273)		(-3.777)		(-3.556)
Observations	23,021	24,154	22,670	23,785	21,174	22,238
Adjusted R-squared	0.156	0.157	0.217	0.213	0.284	0.282
Panel B: 1-HHI						
1-HHI	0.042	0.050*	0.129***	0.157***	0.381***	0.461***
	(1.450)	(1.712)	(2.875)	(3.443)	(5.609)	(6.630)
Oil shock	0.008		-0.015		-0.035	
	(0.327)		(-0.385)		(-0.642)	
1-HHI * Oil shock	-0.009		0.011		0.030	
	(-0.358)		(0.270)		(0.513)	
1-HHI * GFC		-0.126*		-0.301***		-0.567***
		(-1.709)		(-3.021)		(-3.647)
Observations	23,021	24,154	22,670	23,785	21,174	22,238
Adjusted R-squared	0.156	0.157	0.217	0.213	0.286	0.284
Time FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Clustered standard errors	Firm	Firm	Firm	Firm	Firm	Firm