Banking Structures, Liquidity, and Macroeconomic Stability

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Abstract

Banking is increasingly a complex activity. We investigate the output and welfare consequences of banking structures in an economy where lenders use information to screen investment quality and to recover value from failed investments. Complex banking (lenders' joint production of information) eases information production but also facilitates the detection and liquidation of fragile investments. We find that complex banking enhances the resilience to small investment shocks but can amplify the output and welfare responses to large negative shocks. Investment opacity preserves the stabilizing properties of complex banking following small shocks, but increases the chances that complex banking harms welfare after large shocks. The predictions are broadly consistent with evidence from matched bank-firm US data.

Keywords: Banking, Aggregate Fluctuations, Information, Investments

JEL Codes: D83; E44; G21

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

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transformed from being an elementary institution acting independently to becoming affiliates of a complex banking conglomerate.[1] These trends are shown in Appendix Figures A.1 and A.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 paper, we 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, we 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. In our framework we generalize these two modes of organization of banking as a continuum, parameterized by the degree of banking complexity.

We examine the resilience to aggregate shocks of banking regimes characterized by different

[1] This has occurred either through direct ownership in the form of subsidiaries or through cross ownership.

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.

We 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 (overmonitoring). 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. We 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.

In the last part of the paper, we 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, we construct proxies for the complexity of the bank lending pools that extended financing to firms. We 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, we 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.[2]

Related literature The paper 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. 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

[2]We construct two proxies for the complexity of bank lending pools. The first measures the number of times the banks in a syndicated have cooperated with each other in the past, a reflection of their historical tendency to monitor borrowers jointly. The second proxy instead captures the diffusion of loan shares across the lenders participating in a syndicated bank lending pool. The more loan shares are diffuse, in fact, the more we expect banks to engage in joint monitoring of the borrowing firm.

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.

The second related literature investigates the role of credit market information in attenuating or amplifying exogenous shocks (see, e.g., Bernanke and Gertler, 1989; Lang and Nakamura, 1990; Ordonez, 2013; Fajgelbaum et al., 2017; Ambrocio, 2020; Straub and Ulbricht, 2017; Asriyan et al., 2022). 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.

Finally, the paper relates more broadly to the literature on the implications of banking complexity and investment opacity (investment complexity). 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 paper is organized as follows. In Section 2, we present the static model and study its equilibrium. Section 3 examines the impact of banking structures on macroeconomic stability and welfare implications. In Section 4, we extend the analysis to a dynamic setting, performing numerical simulations for the effects of shocks. Section 5 presents empirical evidence on the theoretical predictions using matched bank-firm data from the US credit market. Section 6 concludes. Additional details on derivations and further empirical results are in the Appendix.

2 The Model

2.1 Environment

Agents, Goods, and Technology In congruence with Dang et al. (2017), consider a three period economy populated by a firm, an early agent, a bank, and a late agent. The firm enters the economy in period 0 with no endowment but with a project investment opportunity. The project 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 utility 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. Since the firm has no endowment it needs to raise funds to implement the project. It does so by issuing a claim contingent on the future outcome of the project.

Information and Monitoring We 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 (success or failure) 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, thus preventing the early agent to use the claim to consume in period 1.[3] 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.

We posit that the salvage value of the project is affected by the monitoring efforts exerted by the bank and by the late agent (Diamond and Rajan (2001)). 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 $\alpha \leq \frac{1}{2}$ and s is a strictly positive parameter. We 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. That is, by monitoring collateral, the late agent can better understand the nature of the project.

The parameters α and γ are key in our analysis. We interpret the former as capturing the complexity of the banking structure, and the latter as capturing investment complexity and, hence, opaqueness.[4]

Contractual Structure and Timing 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 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 between the bank and the late agent, where the bargaining power of the bank is θ, with $\theta > \frac{1}{2}$. This contract sets the payment (r_L^g, r_L^b) that the bank

[3] Dang et al. (2017) assumes that the salvage value is zero, thus rendering the claim valueless in case the late agent acquires information and observes that the project will fail.

[4] Gorton and Ordonez (2014) and Dang et al. (2017) have emphasized the role of asset complexity in creating opaque debt. Here, we add to their analysis how banking complexity impacts the salvage value and thus the opaqueness of a complex asset.

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 our analysis, we 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.

2.2 Contracts

Contracts between Bank, Firm, and Early Agent 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 we 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

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

since she can always refuse the contract and consume the endowment. Take it or leave it offer by the bank implies that (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.

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

If a contract is signed between the bank and the late agent, the bank obtains $\lambda \left(A_g - r_L^g\right) + (1-\lambda)\left(A_b - r_L^b\right)$. Failure to sign a contract instead implies that the bank will only have $e - \omega$ units of goods in period 1. Since $e - \omega < c$ by assumption A1, the bank will be liquidated and receive zero 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. We need to make sure that the bank has enough resources for each outcome realization of the project, i.e., we need

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

and

$$A_b \equiv 2e - (\omega + c) + s(\mu_B, \mu_L) \geq r_L^b. \tag{3}$$

Observe that, given r_L, it is weakly optimal to set (3) at equality. This increases the region where (2) holds, with no impact on the maximand, which only depends on r_L. Moreover, as we will show in the next section, the incentives of the late agent to acquire information strictly decrease with r_L^b. We 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 we use r_L^{b*} to rewrite the bargaining problem between the bank and the late agent, and we 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 section we 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.

2.3 Monitoring and Information

Monitoring Choices of Bank and Late Agent We now take the contracts derived in the previous section as given and solve for the monitoring efforts of the bank and the late agent.

We 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

$$\mu_L = \left[(1-\theta)(1-\lambda)s\alpha \right]^{\frac{1}{1-\alpha}} \mu_B. \tag{4}$$

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 we henceforth assume.

We 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 (4) and the fact that $\theta(\lambda x - \omega)$ does not interact with μ_B, we can rewrite $\Pi_B(\mu_B)$ as

$$\widehat{\Pi}_B(\mu_B) = -\frac{1}{2}\mu_B^2 + \theta(1-\lambda)s\left[(1-\theta)(1-\lambda)s\alpha \right]^{\frac{\alpha}{1-\alpha}} \mu_B. \tag{5}$$

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

$$\mu_B^* = \theta(1-\lambda)s\left[(1-\theta)(1-\lambda)s\alpha \right]^{\frac{\alpha}{1-\alpha}}. \tag{6}$$

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

In what follows, we 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 we henceforth assume.

Information on Project Outcome In the previous section, we claimed that the bank holds the belief that the late agent will not obtain information about the outcome of the project. We 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 (4), can be rewritten as

$$z \equiv \omega + c - e \leq F(\mu_B) \equiv s\left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{\alpha}{1-\alpha}} \mu_B. \tag{7}$$

If $A_g > A_b \geq e$ holds, the bank maximizes (5) subject to (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

$$\lambda r_L^{g*} + (1-\lambda) r_L^{b*} \geq -\frac{\gamma}{\mu_L + 1} + \lambda r_L^{g*} + (1-\lambda)e. \tag{8}$$

Observe that the incentives of the late agent to acquire information strictly decrease with r_L^{b*}. Substituting for the values of r_L^{g*}, r_L^{b*} and μ_L, we can rewrite (8) as

$$z \leq G_\gamma(\mu_B) \equiv s\left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{\alpha}{1-\alpha}} \mu_B + \frac{1}{1 + \left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{1}{1-\alpha}} \mu_B} \frac{\gamma}{1-\lambda}. \tag{9}$$

If $A_g > e > A_b$ holds, the bank maximizes (5) subject to (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 $z \leq G_\gamma(\mu_B^*)$. In fact, 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. 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, $\mu_B^+ > \mu_B^*$ (overmonitoring) and $\mu_B^- < \mu_B^*$ (undermonitoring). In the Appendix, we 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 $\mu_L = [(1-\theta)(1-\lambda)s\alpha]^{\frac{1}{1-\alpha}}\mu_B$, 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 μ_B^* if $z \leq G_\gamma(\mu_B^*)$, it chooses $\mu_B^-(z)$ if $z \in \left(G_\gamma(\mu_B^*), \frac{\gamma}{1-\lambda}\right]$, and it chooses not to monitor if $z > \frac{\gamma}{1-\lambda}$.*

Proof. See the Appendix. ■

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.[5] 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

[5]When z is very large and the bank exerts no monitoring effort, our environment essentially collapses into the one considered by Dang et al. (2017), with a zero salvage value and a fixed cost of acquiring 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 the bank's and the late agent's monitoring efforts).

As illustrated also in Figure 1, undermonitoring occurs if the investment complexity γ is relatively large, making the late agent's cost of information acquisition very sensitive to changes in bank monitoring. In contrast, overmonitoring occurs if the investment complexity is low: in such a case the bank will have the incentive to boost the salvage value of the project without risking a large drop in 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 overmonitoring to under monitoring, inducing a substantial drop in the salvage value of the project.

3 Banking Regimes, Shocks, and Output

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

The expected output of the firm is given by

$$y\left(\alpha, \lambda\right) = \lambda x + (1-\lambda) s(\mu_B, \mu_L), \tag{10}$$

that is, it equals the weighted sum of the project output in case of success and of the salvage value in case of failure, weighted by the probabilities of project success and failure, respectively. All else equal, more intense monitoring of the bank and the late agent raises output by boosting salvage values. Using (10), the effect of economic conditions (λ) on output is given by

$$\frac{\partial y}{\partial \lambda} = x - s(\mu_B, \mu_L)\left(\frac{1}{1-\alpha} + \epsilon_{\mu_B, 1-\lambda}\right), \tag{11}$$

where $\epsilon_{\mu_B,1-\lambda} = \frac{\partial \mu_B}{\partial 1-\lambda}\frac{1-\lambda}{\mu_B}$. The monitoring activity of the bank and the late agent can mitigate or amplify the output impact of worse 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 (observe the term $\frac{1}{1-\alpha}$ in parenthesis). 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 (9) binds and the economy is in the constrained information regime, or whether (9) does not bind and the economy is in the unconstrained information regime.

In what follows, we first consider extensive margin effects, studying how the probability that the economy is in the unconstrained region or ends up in the constrained region depends on economic conditions (λ), banking complexity (α), and investment complexity (γ). We then study intensive margin effects, that is, the behavior of monitoring and output when a bank remains in the unconstrained or constrained regions. Finally, we draw conclusions for the resilience of output and welfare.

3.1 Extensive Margin Effects

We study how economic conditions, banking complexity and investment complexity affect the likelihood that the economy enters the constrained information region characterized by bank undermonitoring. Do worse economic conditions (lower λ) push the economy into the constrained information region? And do banking complexity and investment complexity exacerbate or moderate this tendency?

We can prove the following proposition:

Proposition 2 *For a sufficiently high investment complexity, specifically when*

$$\gamma > \gamma_\lambda \equiv \frac{1}{\frac{1}{\theta(1-\lambda)s\Delta^{\frac{1+\alpha}{1-\alpha}}} + \frac{2}{1-\alpha}\frac{1}{1+\theta(1-\lambda)s\Delta^{\frac{1+\alpha}{1-\alpha}}}},$$

where

$$\Delta \equiv (1-\theta)(1-\lambda)s\alpha > 1,$$

a worsening of economic conditions (decline in λ) can push the economy into the information *constrained region and lead to bank undermonitoring, depressing output. This is more likely to occur (i.e., for a smaller drop in λ) when banking complexity is high and when liquidity is tight.*

Proof. See the Appendix. ■

To understand the intuition, recall from Proposition 1 that the region of parameters where the bank chooses the unconstrained monitoring level 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.,

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

As also shown in Figure 1, for example, higher investment complexity expands the unconstrained region information, by making it more costly for the participant bank to acquire information on the project. However, when investment complexity is sufficiently high, any boost to monitoring incentives induced by a reduction in the probability of project success (countercylical monitoring) will have a large positive impact on the participant's bank incentive to acquire information on the nature of the project. In response, the main bank can be forced to depress its monitoring effort (undermonitor) in order to maintain the project opaque and attract the participant bank into the financing of the project. This, in turn, will depress output by shrinking the salvage value of the project. Observe that in principle the main bank could also attempt to raise sharply the salvage value of the project (overmonitor) in order to induce the participant bank to provide funding without incurring in the information acquisition effort. However, when investment complexity is sufficiently high, this overmonitoring strategy is suboptimal relative to the choice of undermonitoring.

Banking complexity exacerbates the fragility of the economy, by making it easier that worse economic conditions push the economy into the constrained information region and induce undermonitoring. The same complementarity in banks' monitoring that favors high salvage values of projects turns out to increase financial fragility in response to negative shocks. By boosting banks' monitoring, in fact, banking complexity reduce the cost associated with the participant's bank information acquisition on the project nature, and the economy can more easily enter the constrained information region.[6]

[6]We can also show that worse economic conditions ... the region of undermonitoring relative to the over-

Finally, the role of liquidity can be key in determining the financial fragility of the economy. When liquidity is tight, and the project is more demanding in terms of financing, it will become harder to satisfy the information revelation constraint, exposing the economy to a higher risk of entering the constrained information, undermonitoring region when λ is lower.

Figure 1 helps better understand the results in Proposition 2, plotting the relevant regions in the (γ, z) space. The frontier between the information unconstrained and constrained regions is upward slopping, indicating that higher investment complexity and lower liquidity tightness relax the information constraint. When economic conditions worsen, the frontier rotates, implying a larger unconstrained region for relatively low values of γ, and a smaller unconstrained region for larger γ values. A similar rotation effect of the frontier occurs when banking complexity is larger.

3.2 Intensive Margin Effects

Having characterized how economic conditions, as well banking and investment complexity, affect the likelihood of hitting the constrained information region, we next turn to characterize the behavior of the economy within the two regions. We start with the unconstrained information region and then consider the constrained region.

Unconstrained Information Region If the bank chooses the unconstrained monitoring level μ_B^*, we have $\epsilon_{\mu_B^*,1-\lambda} = \frac{1}{1-\alpha} > 0$ and worse economic conditions (lower λ) increase the monitoring effort of the bank and the late agent. We can then prove the following:

Proposition 3 *In the unconstrained information region, bank monitoring is always a stabilizer, increasing countercyclically in response to lower economic conditions. In this region, an increase of banking complexity always makes monitoring a better stabilizer, mitigating the output decline in response to worse economic conditions. Investment complexity, instead, has no effect on the stabilizing properties of bank monitoring.*

Proof. Using $\epsilon_{\mu_B^*,1-\lambda}$, we obtain

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

monitoring region, and that this effect is ... by higher banking complexity.

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 higher banking complexity always mitigates the negative 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 unconstrained region where the bank chooses μ_B^*. ■

In the unconstrained information region, the monitoring of the bank and the late agent are more intense when economic conditions are worse: as the probability of project failure is higher, there is a higher incentive for banks to monitor in order to raise the salvage value of projects. In turn, the higher salvage value of projects mitigates 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 while it is not affected by investment complexity. Banking complexity, in fact, boosts the complementarity of banks' monitoring and enhances the monitoring response when project failure becomes more likely.

Constrained Information Region In the constrained information region, the bank can undermonitor or overmonitor, as proved in Proposition 1. In this region, the response of the bank and the late agent's monitoring can act as an attenuator or as an amplifier of worse economic conditions, depending also on banking complexity and investment complexity.

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 be higher when economic conditions are worse (countercyclical monitoring), thus acting as a stabilizer ($\epsilon_{\widehat{\mu}_L,1-\lambda} > 0$) like in the unconstrained regime; alternatively, it can act as an amplifier ($\epsilon_{\widehat{\mu}_L,1-\lambda} < 0$). In what follows we explore these possibilities in the scenario where the bank overmonitors and in the scenario where the bank undermonitors. We can prove the following results:

Proposition 4 *In the constrained information region, bank monitoring will be a stabilizer like in the unconstrained region when banks overmonitor, increasing countercyclically in response to worse economic conditions. When banks undermonitor, bank monitoring can instead become destabilizing, dropping, and magnifying the output loss, in response to worse economic conditions. In the undermonitoring region, higher banking complexity and investment complexity can mitigate any destabilizing effect of bank monitoring).*

Overmonitoring 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.

Banking complexity and investment complexity have quite a nuanced effect on the stabilizing function of bank monitoring in the overmonitoring region. After some algebra, 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 higher banking complexity amplifies the output drop induced by worse economic conditions, diluting the stabilizing function of bank monitoring.

As for investment complexity, we obtain

$$\frac{\partial^2 y^+}{\partial\lambda\partial\gamma} = \frac{z}{\alpha(1-\lambda)(1-\theta)\left(\mu_L^+ + 1\right)^2}\left[\frac{\mu_L^+}{z - \frac{2\mu_L^+ + 1}{\left(\mu_L^+ + 1\right)^2}\frac{\gamma}{1-\lambda}}\right]^2\frac{\frac{\left(\mu_L^+ + 1\right)^2}{\alpha(1-\theta)} + \gamma}{\frac{\left(\mu_L^+ + 1\right)^2}{\alpha(1-\theta)} - \gamma}. \tag{12}$$

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 again amplifies the output response.

Undermonitoring 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, we are 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. 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 higher banking complexity amplifies the output response, diluting the stabilizing property of monitoring. The opposite happens when $\gamma > \frac{\left(\mu_L^* + 1\right)^2}{(1-\theta)\alpha}$.

As for investment complexity,

$$\frac{\partial^2 y^-}{\partial \lambda \partial \gamma} = \frac{z}{\alpha(1-\lambda)(1-\theta)\left(\mu_L^- + 1\right)^2} \left[\frac{\mu_L^-}{z - \frac{2\mu_L^- + 1}{\left(\mu_L^- + 1\right)^2} \frac{\gamma}{1-\lambda}} \right]^2 \frac{\frac{\left(\mu_L^- + 1\right)^2}{\alpha(1-\theta)} + \gamma}{\frac{\left(\mu_L^- + 1\right)^2}{\alpha(1-\theta)} - \gamma}. \tag{13}$$

As in the case of banking 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 higher investment complexity amplifies the output response. The opposite happens when $\gamma > \frac{\left(\mu_L^* + 1\right)^2}{(1-\theta)\alpha}$. Proposition 4 summarizes our results for the constrained information region.

3.3 Output Resilience to Small and Large Shocks

The above results yield implications for the output resilience to worse economic conditions and for the influence of banking complexity and investment complexity on such resilience. Consider a scenario in which an economy in the unconstrained information region is hit by a worsening in economic conditions (a drop in λ).

Small shocks: When the shock is sufficiently small, i.e. the λ drop is small, the economy will remain in the unconstrained information region. Intuitively, bank monitoring will remain moderate and there will be no need for banks to be constrained by the need to prevent 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 the small shock.

Large shocks: When the shock is sufficiently large, i.e. the λ drop is severe, the countercyclical behavior of bank monitoring, and the resulting increase in late agents' incentive to acquire information on projects, will start to generate a need for banks to hide information. That is, 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, the bank may choose to overmonitor, and bank monitoring can continue to remain countercyclical, acting as a stabilizer. However, in some scenarios the bank may opt for undermonitoring, and monitoring become instead procyclical, turning 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 complex banking systems are a better stabilizer for small shocks ("better resilience"), but can become worse stabilizers, and possibly even amplifiers, for large shocks ("weaker resilience"). We now summarize these patterns with the help of a numerical simulation.

3.4 Numerical Simulations

Consider equation (9), reported here for convenience:

$$z \leq G_{\gamma}(\mu_B) \equiv s\left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{\alpha}{1-\alpha}}\mu_B + \frac{1}{1+\left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{1}{1-\alpha}}\mu_B}\frac{\gamma}{1-\lambda}. \tag{14}$$

For all parameters fixed and varying λ, $G_\gamma(\mu_B)$ is a parabolic function. Thus, for a sufficiently low value of λ equation (14) is binding ($G_\gamma(\mu_B^*) = z$). We arrive at the possible two root solutions μ_B^+ and μ_B^-. As the bank is profit-maximizing, we establish a threshold condition for the choice of undermonitoring over overmonitoring from (5) as

$$\widehat{\Pi}_B(\mu_B^-) > \widehat{\Pi}_B(\mu_B^+),$$

and vice-versa if the inequality is reversed.

In our numerical simulations, we fix all parameters while varying λ and consider two different banking regimes (α_1, α_2), with $\alpha_2 > \alpha_1$ and a higher α reflecting higher banking complexity.[7] Table 2 summarizes the chosen parameter values.

Figures (3a)-(3c) plot the level of output, bank monitoring and the right-hand side of the information constraint for the two different levels of banking complexity. Figure (3a) aligns with the extensive margin result of Proposition (2): the complex α_2-banking regime is constrained at an earlier threshold (i.e., for a higher value of λ). When the economy hits the constrained information region, the bank chooses to undermonitor, and thereafter, for even lower λ values, monitoring declines.[8] Accordingly, salvage values and output decline, too. In line with Proposition 4, in the undermonitoring region, the decline of output is slower under the complex banking regime.

3.5 Welfare

Welfare is given by 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 (4), welfare can be rewritten as

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

[7]We suppress additional notations and characterize our functional objects by banking complexity (α_1, α_2).

[8]Additional figures found in Appendix A provide additional graphs for α_1 and α_2, respectively.

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 extensive margin, and 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, in the unconstrained region the bank always monitors less than the welfare maximizing level, because it does not fully internalize the 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 the bank monitors less than the welfare maximizing level in the region where the information constraint 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 it moves into the information constrained region (in a knife-edge case, achieving the optimal monitoring).

Turning to the intensive margin, we can assess the impact of economic conditions on welfare, exploiting the results obtained for output. Again consider first the unconstrained information region. In this region, as shown above, output drops as long as

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

In turn, welfare is given by output net of the monitoring costs of bank and late agent. 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 is lower. Together with the output drop this implies that welfare necessarily shrinks in this region ($\frac{\partial \mathcal{W}}{\partial \lambda} > 0$). 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 gap between equilibrium monitoring and the welfare-maximizing monitoring 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 gap between equilibrium monitoring and the welfare-maximizing monitoring will widen. In fact, when there is undermonitoring, banks' monitoring is depressed further below the optimal level. Moreover, optimal monitoring varies countercyclically whereas, if the bank undermonitors, monitoring drops as λ drops (i.e., moves procyclically), widening the welfare gap. Consider next the case in which the bank overmonitors in the constrained information region. As proved above, in this case there will be an improvement in welfare and possibly a narrowing of the gap between equilibrium monitoring and the welfare-maximizing monitoring.

once the economy enters the constrained region. In fact, the equilibrium monitoring will move closer to the optimal monitoring level.

4 Dynamic Setting

Layout and Equilibrium In what follows, we extend the economy into an infinite horizon. The environment is largely as in our baseline static set up, but we collapse our three period setting into a one-period economy with two sub-periods. To streamline the exposition, we also 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.

A 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. In the above, $|\rho| < 1$ is a persistence parameter, $s > 0$ is a scale parameter and $\kappa < 1-\alpha$ is 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[9] and ε_t denotes a shock in period t that follows an AR(1) process given as

$$\varepsilon_t = \nu \varepsilon_{t-1} + \upsilon_t.$$

Where $|\nu| < 1$ and υ_t is IID and distributed over $N(0, \sigma^2)$ and ε_1 is given. 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

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

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

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

[9]We note the observation for $\rho = 1$ and $\kappa = 0$ the infinite horizon economy simply boils down to a sequence of baseline finite horizon economies.

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, $G''_{\gamma,t}(\mu_{Bt}) > 0$. We then have all the element to adapt Proposition 1 to the dynamic setting. Proposition 6 summarizes our result.

Proposition 5 *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 $\mu_{Lt} = \left[(1-\theta)(1-\lambda_t)s_t\alpha\right]^{\frac{1}{1-\alpha}}\mu_{B_t}$, 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, we are interested in examining how shocks to economic conditions (the probability of project success λ) impact on the monitoring effort of the bank and the late agent and on output, and how banking 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 of projects.

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_B^{ss}. Now, we can rewrite s_t as

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

which implies

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

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 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 a 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. Moreover, 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 steady state. In order to ensure that this is the case, henceforth we posit that $\kappa \geq \overline{\kappa}$.

Response to Shocks We can now examine the effects of shocks to the probability of project success. We consider a scenario where the economy is initially in the steady-state equilibrium and a negative shock hits the probability of project success in period t. Similar to the numerical simulations in the static setting we consider two banking regimes; Table 4 summarizes the chosen parameter values. Further, we consider an initial recessionary shock followed by a one-time shock:

$$\varepsilon_1 = 0.0245,$$

$$\nu_2 = 0.0235.$$

Figure 5 plots the impulse response functions (percentage deviations from steady state) for bank monitoring, salvage value, and output, as well as a supplementary graph for the $G(\mu^*_{Bt})$ function which serves to understand when the economy is in the constrained information region. The α_1-banking regime is represented in red while the α_2-banking regime is represented in black.

The shock process $\{\varepsilon_{1t}\}$ describes a relatively persistent recessionary shock. The low banking complexity economy (red line) never enters the constrained information region. Monitoring rises countercyclically in the first two periods, and this attenuates the output drop. As the shock fades in subsequent periods, monitoring reverts to the steady state level. The high banking complexity economy (black line) exhibits a stronger countercyclical response of monitoring. This dampens the negative output impact of the shock more than in the low banking complexity economy. However, the substantial increase in monitoring pushes the economy into the constrained information region in the third period. The bank then chooses to undermonitor, and this explains the severe drop in monitoring. Due to undermonitoring, the output recovery is slower than in the low banking complexity economy. That is, high banking complexity implies a milder recession in the immediate aftermath of the shock but also a slower recovery.

5 Empirical Evidence

We test empirically the implications of the theoretical model on the influence of banking structures for the response to shocks. Based on the predictions of the model our goal is twofold. 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. We are also interested whether any 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 present the empirical findings.

5.1 Setting, Measurement, and Methodology

Institutional setting 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.

Measuring banking complexity We construct proxies for the complexity of the bank lending pools from which firms obtain financing. 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 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 a 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.

Firm-level and loan-level variables 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 include time fixed effects to capture a variety of other aggregate phenomena that occurred during the sample period.[10] In alternate tests, we replace bank and time fixed effects with bank*time fixed effects.

Aggregate shocks 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 aggregate 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

[10] When inserting time fixed effects, we can be unable to estimate the direct effect of aggregate shocks on firm growth (if the time fixed effects absorb the effects of the shock). In our analysis, however, we are primarily interested in the interaction between banking complexity and aggregate shocks.

expected oil price. In robustness checks, we also weigh oil price shocks by the exposure of the firm's sector 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 occurred.

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

$$\begin{aligned}\text{Firm}_{flt} =& \alpha + \beta \text{Complex}_{bft} + \gamma \text{Shock}_t + \delta(\text{Complex}_{bft} \times \text{Shock}_t) + \eta X_{ft} \\ &+ \zeta Y_{lt} + \mu_b + \mu_l + \mu_{l'} + \mu_f + \mu_t + \epsilon_{flt}.\end{aligned} \tag{15}$$

In equation (15), 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 lending pool 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 include 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.

Summary statistics Appendix Table C.1 reports sample summary statistics. The firms are typically medium-sized or large. On average, the growth rate of firms' total assets over the sample period equals -6%, with a sizeable heterogeneity across firms. The mean growth rate of firms' fixed assets (our measure of firm investment) is -5.9%. The average number of banks that lend to a firm in a syndicate is 13. Our proxies for the degree of banking complexity exhibit substantial 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%. As for the incidence of aggregate shocks in the sample, about 8% of the loans are extended during the Great Financial Crisis, while 11.8% are originated during a negative oil shock episode.

The empirical literature treats the share of the syndicated loan retained by banks as a proxy for monitoring incentives (Sufi, 2007; Ivashina, 2009). Appendix Figure A.3 plots the evolution over time of the average share held by banks together with 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.

5.2 Estimation Results

Baseline estimates Tables 5 and 6 display the baseline estimation results. In line with expectations, the estimates consistently point to a negative impact of aggregate contractionary 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 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 lending pools appear to amplify the negative response of firms' asset growth and investment. These 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. They 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.[11]

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

IV estimates Despite the broad range of loan and firm characteristics and fixed effects included in the specifications, the endogeneity of the lending pools 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

[11] The coefficient estimates on the controls are broadly in line with expectations. For example, a higher firm leverage is associated with a lower growth rate of firms.

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 collected data on M&A from the FRB and identified the banks in DealScan. Then we constructed 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. Thus, we identify a treatment effect using only information from the target bank. 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 7 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 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 controls. Similarly in columns III-IV, where we use the *1-HHI*.[12] The first-stage results reveal a strong, positive relationship between the instrument and bank complexity: 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) confirm the conclusions drawn from the granular fixed effects estimations. Conditional on the included controls, the endogeneity concerns discussed earlier are not material enough to undermine the

[12] The sample set of columns I and II is the same, and similar for columns III-IV.

interpretation.

The role of investment complexity and profitability 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 8 and 9 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 between banking complexity and large shocks is larger when investments are informationally less complex. Appendix C Table C.2 also re-estimates the baseline results after restricting the sample to firms with relatively lower profitability (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 banking complexity. We observe that the positive impact of banking complexity is generally attenuated for lower profitability firms.

Firm-level aggregation In the loan-level analysis, we observe whether bank complexity enhances firms' resilience to small negative aggregate shocks while reducing their resilience to large shocks. However, the analysis cannot uncover potential substitution 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 offset 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. Appendix C Tables C.3 and C.4 indicates real effects in the second year and after.

6 Conclusion

This paper studies the output and welfare consequences of banks and banking structures in an economy where banks both produce and conceal information on investments. In our 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. We 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.

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Figure 1: Relationship between liquidity and investment complexity

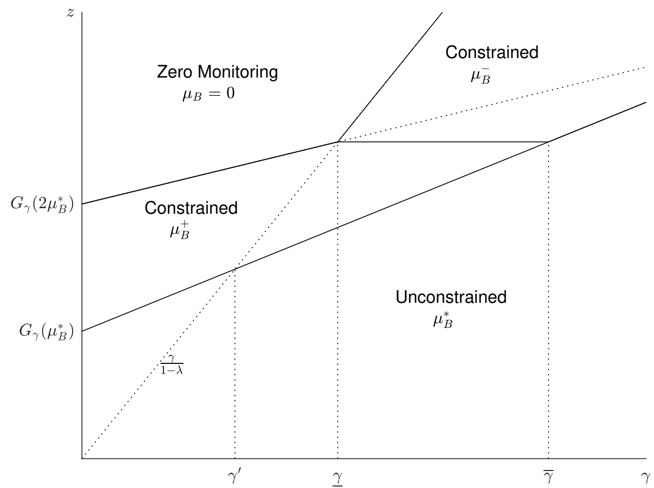
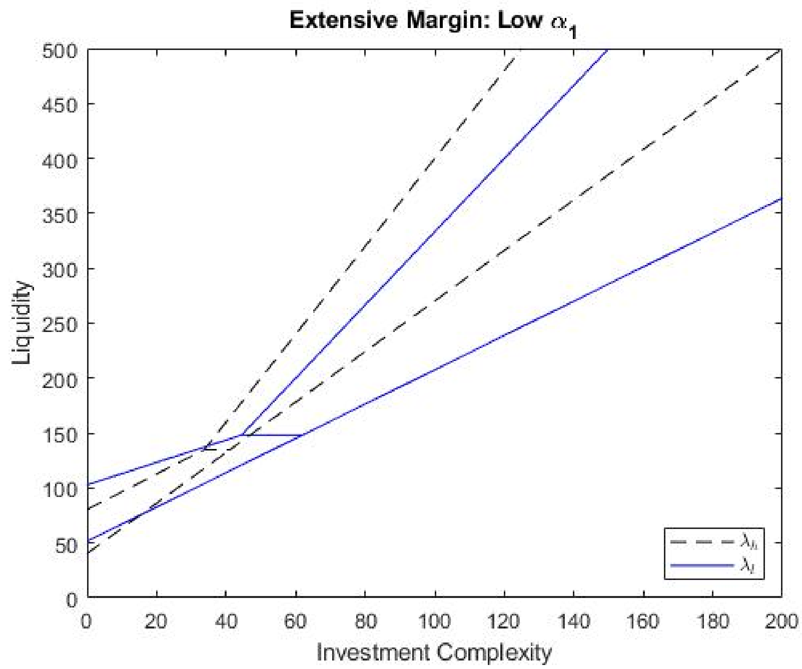


Figure 2: Extensive Margins

(a)



(b)

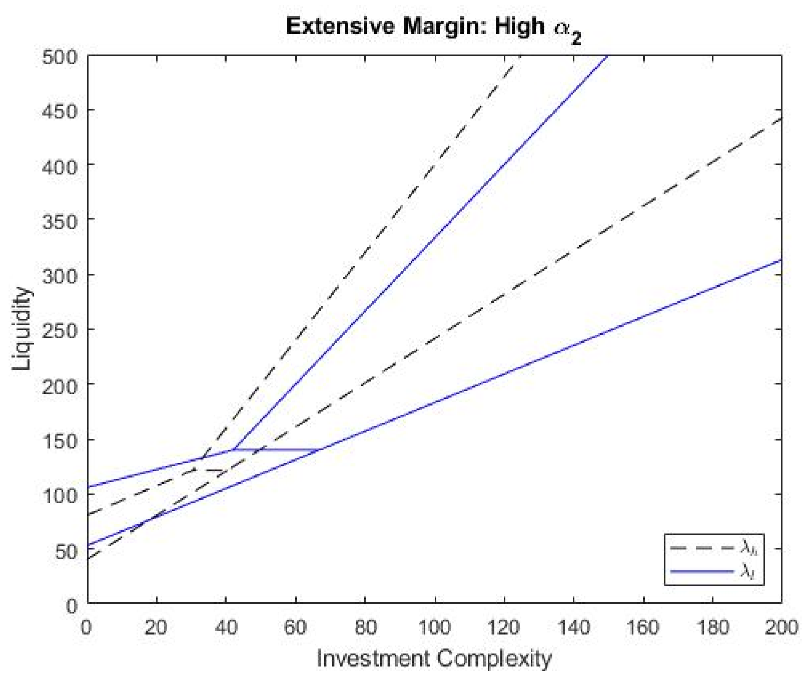
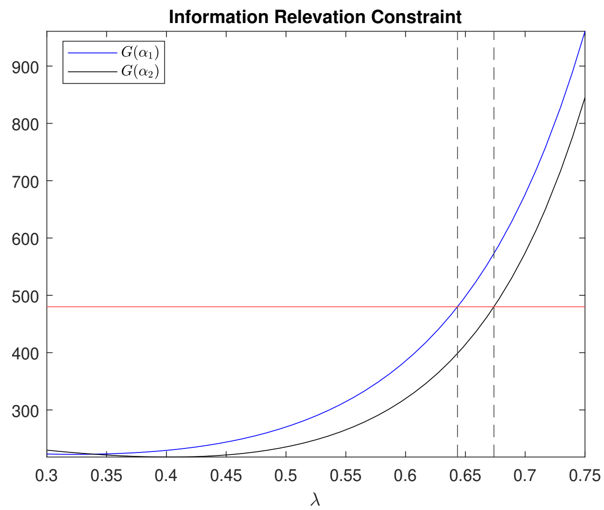


Figure 3: Intensive Margins

(a)



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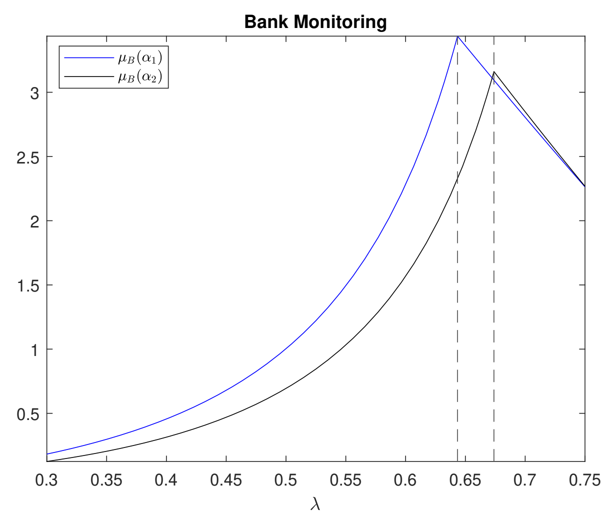


(c)

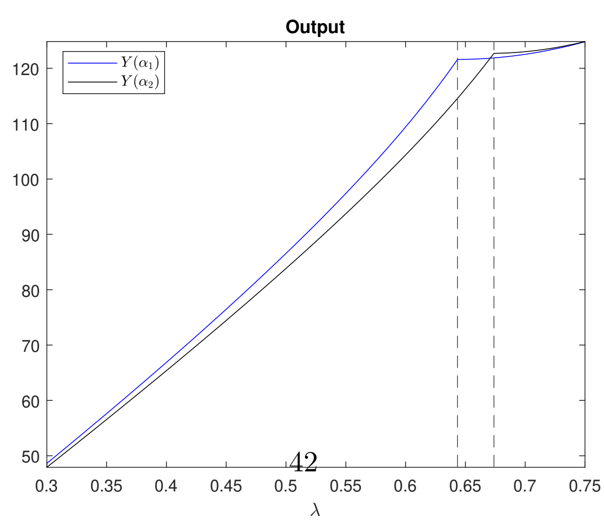
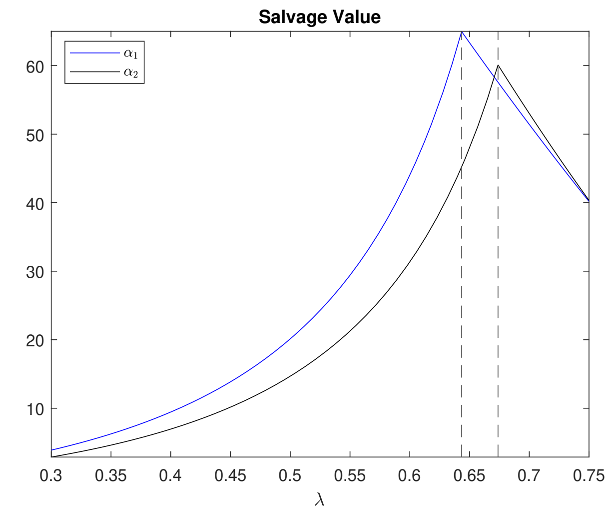


Figure 4: Intensive Margins

(a)



(b)

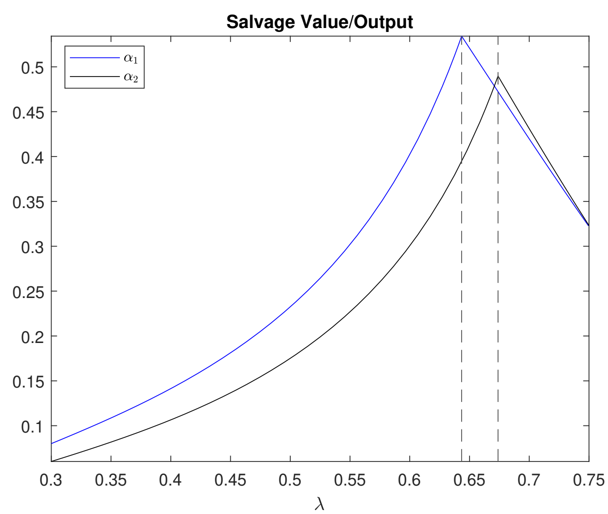


Figure 5: Responses to Recessionary Shock in Dynamic Economies

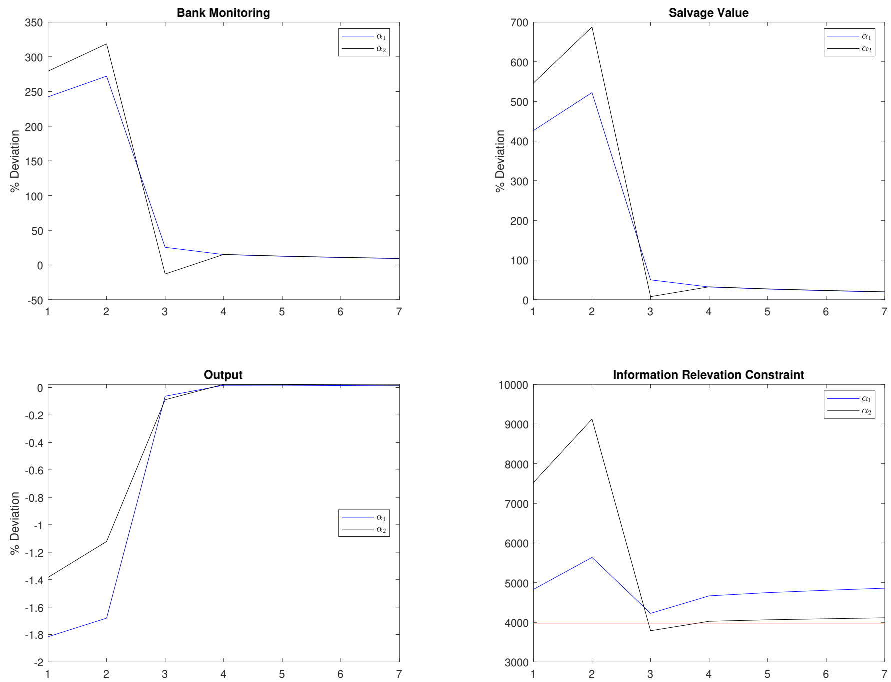


Table 1: Extensive Margin: Parameters and Values

Parameter	Description	Value
α_1	Low banking complexity	0.15
α_2	High banking complexity	0.20
θ	Nash bargaining	0.51
s	Asset price shifter	21
λ_h	High probability	0.75
λ_l	Low probability	0.70

Table 2: Intensive Margin: Parameters and Values

Parameter	Description	Value
α_1	Banking complexity	0.15
α_2	Banking complexity	0.20
θ	Nash bargaining	0.51
γ	Investment complexity	400
z	Liquidity constraint	480
ω	Project investment	70

Table 3: Intensive Margin: Average Values across λ

Banking Complexity	Parameter	Description	Value
α_1	μ_L	Outside investor monitoring	0.8479
α_1	μ_B	Bank monitoring	1.2216
α_1	$s(\mu_B, \mu_L)$	Salvage value	24.2859
α_1	y	Output	91.861
α_1	y/ω	Gross Expected Return	1.3123
α_2	μ_L	Outside investor monitoring	0.8213
α_2	μ_B	Bank monitoring	0.8450
α_2	$s(\mu_B, \mu_L)$	Salvage value	17.6442
α_2	y	Output	88.704
α_2	y/ω	Gross Expected Return	1.2672

Table 4: Dynamic: Parameters and Values

Parameter	Description	Value
α_1	Banking complexity	0.35
α_2	Banking complexity	0.40
θ	Nash bargaining	0.51
κ	Information generation	0.20
ρ	Persistence	0.20
s	Asset price shifter	235
ν	AR 1 Parameter	0.04
γ	Investment complexity	350
λ	Long-run probability	0.98
z	Liquidity constraint	3980
x	Project profitability	2806

Table 5: Banking Complexity and Firms' Resilience to Aggregate Shocks

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

This table reports coefficient estimates and robust (clustered by bank) standard errors for the effects of shocks on firms' asset growth and the influence of bank lending pool complexity on these effects. In all the regressions the dependent variable is the percentage growth of firms' total assets. In columns I-IV, banking complexity is captured by the number of past interactions between banks in the syndicate in the previous five years. In columns V-VIII, banking complexity is captured by the number 1-HHI, where HHI is the Herfindhal index of concentration of the syndicated loan. In columns I, III, V, VII aggregate shocks are captured by oil price increases above the expected oil price. In columns II, IV, VI, VIII aggregate shocks are captured by the Great Financial Crisis (GFC). Loan controls include the loan maturity, the loan spread, and a dummy for whether the loan is a refinancing of a prior loan. Firm controls include the firm's credit rating, leverage and ROA. All the regressions include loan purpose and loan type fixed effects, and firm fixed effects. Columns I-II and V-VI also include bank and time fixed effects, while columns III-IV and VII-VIII include bank*time fixed effects. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Table 6: Banking Complexity and Firms' Resilience to Aggregate Shocks (cont.)

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

This table reports coefficient estimates and robust (clustered by bank) standard errors for the effects of shocks on firms' fixed asset growth and the influence of bank lending pool complexity on these effects. In all the regressions the dependent variable is the percentage growth of firms' fixed assets. In columns I-IV, banking complexity is captured by the number of past interactions between banks in the syndicate in the previous five years. In columns V-VIII, banking complexity is captured by the variable 1-HHI, where HHI is the Herfindhal index of concentration of the syndicated loan. In columns I, III, V, VII aggregate shocks are captured by oil price increases above the expected oil price. In columns II, IV, VI, VIII aggregate shocks are captured by the Great Financial Crisis (GFC). Loan controls include the loan maturity, the loan spread, and a dummy for whether the loan is a refinancing of a prior loan. Firm controls include the firm's credit rating, leverage and ROA. All the regressions include loan purpose and loan type fixed effects, and firm fixed effects. Columns I-II and V-VI also include bank and time fixed effects, while columns III-IV and VII-VIII include bank*time fixed effects. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Table 7: Banking Complexity and Firms' Resilience to Shocks: 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

This table reports coefficient estimates and and t-statistics (in brackets) from a 2SLS estimation. The first-stage regressions are given in Panel A. The instrument is the bank complexity of the target bank (acquired) one year before the loan origination. Panel B reports the second-stage regressions for each category. In the second stage regressions, the dependent variable is the percentage growth of firms' total assets. In columns I and II, the banking complexity is captured by the number of interactions of the banks in the syndicate lending pool in the past five years. In columns III and IV, the banking complexity is captured by the variable 1-HHI, where HHI is the Herfindhal index of concentration of the syndicated loan. In columns I and III aggregate shocks are captured by oil price increases above the expected oil price. In columns II and IV aggregate shocks are captured by the Great Financial Crisis (GFC). Loan controls include the loan maturity, the loan spread, and a dummy for whether the loan is a refinancing of a prior loan. Firm controls include the firm's credit rating, leverage and ROA. All the regressions include loan purpose and loan type fixed effects, and different fixed affects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Table 8: Banking Complexity, Investment Complexity, and Firms' Resilience to Shocks

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

This table reports coefficient estimates and robust (clustered by bank) standard errors for the effects of shocks on firms' fixed asset growth and the influence of bank lending pool complexity and investment complexity on these effects. In columns I-IV the dependent variable is the percentage growth of firms' total assets; in columns V-VIII the dependent variable is the percentage growth of firms' fixed assets. In all regressions, banking complexity is captured by the number of interactions of the banks in the syndicate lending pool in the past five years. In all columns aggregate shocks are captured by the Great Financial Crisis (GFC). Investment complexity is measured by the degree of proximity of the loan portfolio of the lead arranger and the participant bank. Loan controls include the loan maturity, the loan spread, and a dummy for whether the loan is a refinancing of a prior loan. Firm controls include the firm's credit rating, leverage and ROA. All the regressions include loan purpose and loan type fixed effects, and firm fixed effects. Columns I-II and V-VI also include bank and time fixed effects, while columns III-IV and VII-VIII include bank*time fixed effects. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

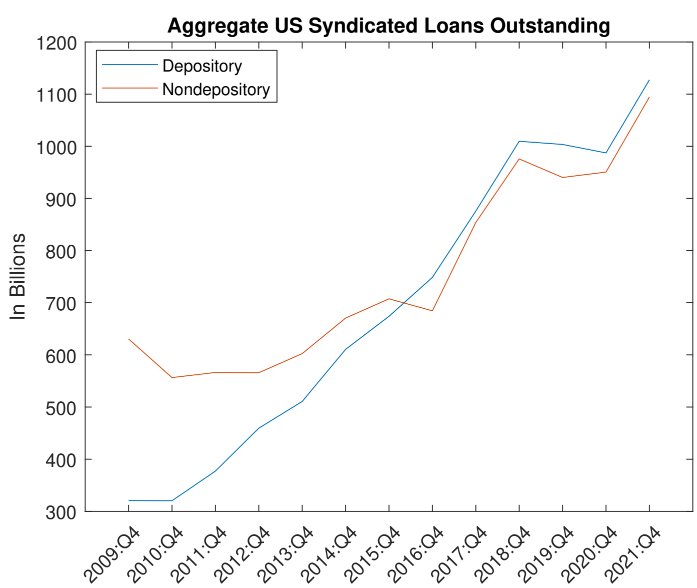
Table 9: Banking Complexity, Investment Complexity, and Firms' Resilience to Shocks (cont.)

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

This table reports coefficient estimates and robust (clustered by bank) standard errors for the effects of shocks on firms' fixed asset growth and the influence of bank lending pool complexity and investment complexity on these effects. In columns I-IV the dependent variable is the percentage growth of firms' total assets; in columns V-VIII the dependent variable is the percentage growth of firms' fixed assets. In all regressions, banking complexity is captured by the variable 1-HHI, where HHI is the Herfindhal index of concentration of the syndicated loan. In all columns aggregate shocks are captured by the Great Financial Crisis (GFC). Investment complexity is measured by the degree of proximity of the loan portfolio of the lead arranger and the participant bank. Loan controls include the loan maturity, the loan spread, and a dummy for whether the loan is a refinancing of a prior loan. Firm controls include the firm's credit rating, leverage and ROA. All the regressions include loan purpose and loan type fixed effects, and firm fixed effects. Columns I-II and V-VI also include bank and time fixed effects, while columns III-IV and VII-VIII include bank*time fixed effects. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

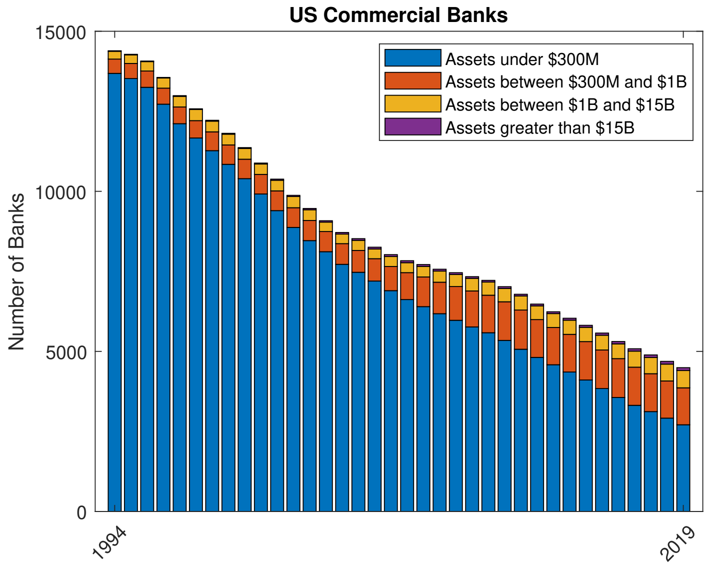
Appendix A

Figure A.1



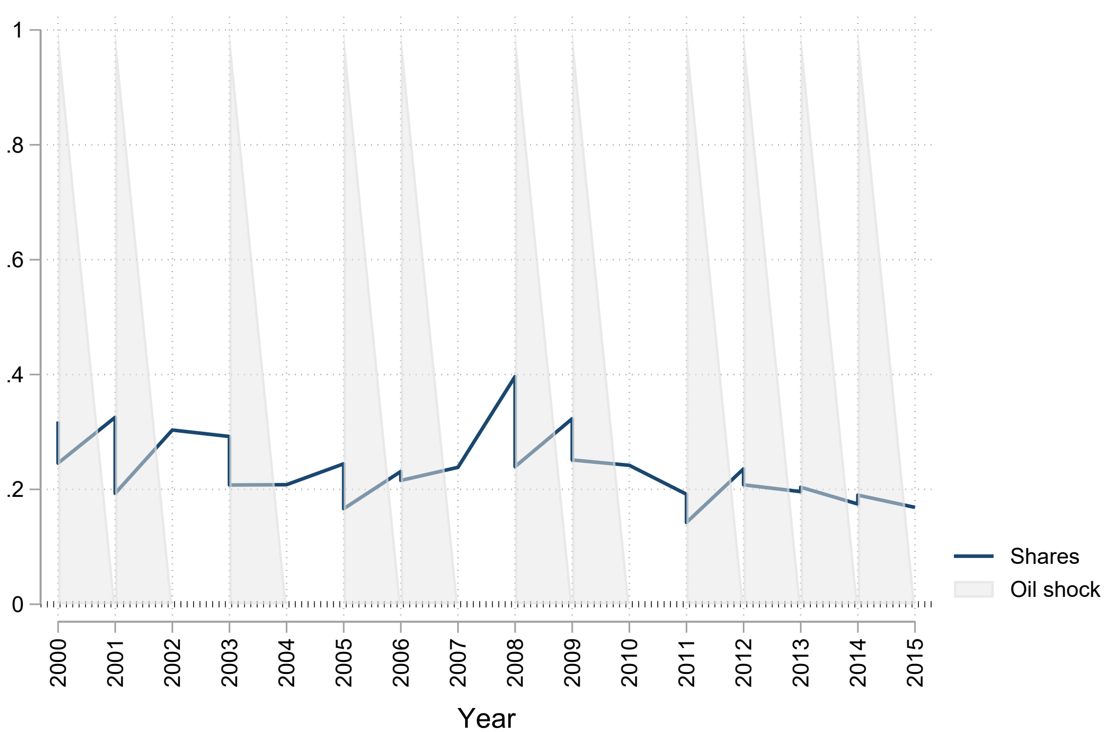
Source: SNC Program, Board of Governors of the Federal Reserve System

Figure A.2



Source: Federal Reserve Bank of St. Louis

Figure A.3: Monitoring and oil shocks



Appendix B

Data Appendix 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.

Appendix C

Table C.1: Experience and the likelihood of being chosen as a lead arranger

	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

The table provides descriptive statistics for the main variables used in analysis.

Table C.2: Banking Complexity and Firms' Resilience to Shocks: 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

This table reports coefficient estimates and robust (clustered by bank) standard errors for the effects of shocks on firms' fixed asset growth and the influence of bank lending pool complexity. Firm profitability group is a dummy equals one if the firm's return on assets is below the sample median. In Panel A, banking complexity is captured by the number of interactions of the banks in the syndicate lending pool in the past five years. In Panel B, the banking complexity is captured by the variable 1-HHI, where HHI is the Herfindhal index of concentration of the syndicated loan. In columns I and III aggregate shocks are captured by oil price increases above the expected oil price. In columns II and IV aggregate shocks are captured by the Great Financial Crisis (GFC). Loan controls include the loan maturity, the loan spread, and a dummy for whether the loan is a refinancing of a prior loan. Firm controls include the firm's credit rating, leverage and ROA. All the regressions include loan purpose and loan type fixed effects, and different levels of fixed effects as noted in the lower part of the table. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Table C.3: Banking Complexity and Firms' Resilience to Aggregate Shocks: Firm level evidence

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

This table reports coefficient estimates and robust (clustered by firm) standard errors for the effects of shocks on firms' asset growth and the influence of bank lending pool complexity on these effects. We aggregate a sample of U.S. syndicated loans for firms covered in Dealscan at the firm-year level. In all the regressions the dependent variable is the percentage growth of firms' total assets. In Panel A, banking complexity is captured by the number of past interactions between banks in the syndicate in the previous five years. In Panel B, banking complexity is captured by the number 1-HHI, where HHI is the Herfindhal index of concentration of the syndicated loan. In columns I, III, V aggregate shocks are captured by oil price increases above the expected oil price. In columns II, IV, VI aggregate shocks are captured by the Great Financial Crisis (GFC). Loan controls include the loan maturity, the loan spread, and a dummy for whether the loan is a refinancing of a prior loan. Firm controls include the firm's credit rating, leverage and ROA. All the regressions include loan purpose and loan type fixed effects, and different levels of fixed effects as noted in the lower part of the table. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Table C.4: Banking Complexity and Firms' Resilience to Aggregate Shocks: Firm level evidence (cont.)

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

This table reports coefficient estimates and robust (clustered by firm) standard errors for the effects of shocks on firms' asset growth and the influence of bank lending pool complexity on these effects. We aggregate a sample of U.S. syndicated loans for firms covered in Dealscan at the firm-year level. In all the regressions the dependent variable is the percentage growth of firms' fixed assets. In Panel A, banking complexity is captured by the number of past interactions between banks in the syndicate in the previous five years. In Panel B, banking complexity is captured by the number 1-HHI, where HHI is the Herfindhal index of concentration of the syndicated loan. In columns I, III, V aggregate shocks are captured by oil price increases above the expected oil price. In columns II, IV, VI aggregate shocks are captured by the Great Financial Crisis (GFC). Loan controls include the loan maturity, the loan spread, and a dummy for whether the loan is a refinancing of a prior loan. Firm controls include the firm's credit rating, leverage and ROA. All the regressions include loan purpose and loan type fixed effects, and different levels of fixed effects as noted in the lower part of the table. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Appendix D

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

$$\max_{0\leq r_L^g \leq 2e-(\omega+c)+x-\frac{e-c}{\lambda}} \left\{ \lambda^\theta \left[2e-(\omega+c)+x-\frac{e-c}{\lambda}-r_L^g \right]^\theta \left[\lambda r_L^g + (1-\lambda) r_L^{b*} - e \right]^{1-\theta} \right\}. \tag{16}$$

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 (16) 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

$$\mu_B^+(z) + \mu_B^-(z) \leq 2\theta(1-\lambda)s\left[(1-\theta)(1-\lambda)s\alpha\right]^{\frac{\alpha}{1-\alpha}}. \tag{17}$$

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

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

We can then rewrite (17) as

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

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

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

Lastly, if $\gamma \in \left(\underline{\gamma}, \overline{\gamma}\right)$ and $z \in (G_\gamma(\mu_B^*), G_\gamma(0))$, the bank chooses $\mu_B^+(z)$ if $z \leq \frac{\gamma}{1-\lambda}$ 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 $\left(G_\gamma(\mu_B^*), \frac{\gamma}{1-\lambda}\right]$, we obtain that welfare is constant for all $z \leq G_\gamma(\mu_B^*)$, it is strictly decreasing in the interval $\left(G_\gamma(\mu_B^*), \frac{\gamma}{1-\lambda}\right]$, and it converges to λx for all $z \geq \frac{\gamma}{1-\lambda}$.

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 (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

$G_\gamma(\mu_B^*) > \frac{2\mu_L^*+1}{(\mu_L^*+1)^2}\frac{\gamma}{1-\lambda}$, 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.

Appendix C Extensive Margin Effects

The combination of assumption A2 and $\alpha < \frac{1}{2}$ requires

$$\frac{1}{(1-\theta)(1-\lambda)s} < \alpha < \frac{1}{2}.$$

A necessary restriction on parameters ensuring that this region is non-empty is

$$0 < \lambda < 1 - \frac{2}{(1-\theta)s}, \quad \frac{1}{2} < \theta < 1 - \frac{2}{s}, \quad \text{and} \quad s > 4,$$

where we also used $\theta > \frac{1}{2}$.

We start by examining the impact of $(\lambda, \alpha, \gamma)$ on the size of the unconstrained region. The frontier of the unconstrained region is given by

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

where

$$\Delta \equiv (1-\theta)(1-\lambda)s\alpha > 1,$$

given assumption A2.

We have

$$f_\gamma(\lambda, \alpha, \gamma) = \frac{1}{(1-\lambda)\left[1+\theta(1-\lambda)s\Delta^{\frac{1+\alpha}{1-\alpha}}\right]} > 0,$$

and the unconstrained region expands with γ.

To determine the impact of λ, let us examine

$$\mu_L^* = \theta(1-\lambda)s\Delta^{\frac{1+\alpha}{1-\alpha}}.$$

We have

$$\frac{\partial \mu_L^*}{\partial \lambda} = -\theta s \Delta^{\frac{1+\alpha}{1-\alpha}} + \theta(1-\lambda)s\frac{\partial \Delta^{\frac{1+\alpha}{1-\alpha}}}{\partial \lambda},$$

where

$$\frac{\partial \Delta^{\frac{1+\alpha}{1-\alpha}}}{\partial \lambda} = -\frac{1+\alpha}{1-\alpha}\Delta^{\frac{1+\alpha}{1-\alpha}}\frac{1}{1-\lambda}.$$

As a result

$$\frac{\partial \mu_L^*}{\partial \lambda} = -\frac{2\theta s \Delta^{\frac{1+\alpha}{1-\alpha}}}{1-\alpha},$$

or

$$\frac{\partial \mu_L^*}{\partial (1-\lambda)}\frac{1-\lambda}{\mu_L^*} = \frac{2}{1-\alpha}.$$

We obtain

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

and $f_\lambda(\lambda,\alpha,\gamma)$ if and only if

$$\gamma > \gamma_\lambda \equiv \frac{1}{\frac{1}{\theta(1-\lambda)s\Delta^{\frac{1+\alpha}{1-\alpha}}} + \frac{2}{1-\alpha}\frac{1}{1+\theta(1-\lambda)s\Delta^{\frac{1+\alpha}{1-\alpha}}}}.$$

If investment complexity is relatively large, the unconstrained region expands with λ, otherwise it contracts with λ.

To determine the impact of α, we first determine

$$\frac{\partial \Delta^{\frac{1+\alpha}{1-\alpha}}}{\partial \alpha} = \frac{1+\alpha+\ln \Delta^{\frac{2\alpha}{1-\alpha}}}{1-\alpha}\frac{\Delta^{\frac{1+\alpha}{1-\alpha}}}{\alpha},$$

which implies

$$\frac{\partial \mu_L^*}{\partial \alpha} = \theta(1-\lambda)s\frac{1+\alpha+\ln \Delta^{\frac{2\alpha}{1-\alpha}}}{1-\alpha}\frac{\Delta^{\frac{1+\alpha}{1-\alpha}}}{\alpha},$$

or

$$\frac{\partial \mu_L^*}{\partial \alpha}\frac{\alpha}{\mu_L^*} = \frac{1+\alpha+\ln\Delta^{\frac{2\alpha}{1-\alpha}}}{1-\alpha}.$$

We obtain

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

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

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

If investment complexity is relatively low, the unconstrained region expands with α, otherwise it contracts with α.

We now examine how changes in γ and α impact $f_\lambda(\lambda,\alpha,\gamma)$. We have

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

and an increase in investment complexity amplifies the effect of λ on the size of the unconstrained region. If $f_\lambda(\lambda,\alpha,\gamma) > 0$, this means that the contraction of the unconstrained region caused by a decrease in λ is larger when investment complexity increases. If $f_\lambda(\lambda,\alpha,\gamma) < 0$, this means that the expansion of the unconstrained region caused by a decrease in λ is smaller when investment complexity increases.

We also have

$$f_{\alpha\lambda}(\lambda,\alpha,\gamma) = -\frac{1}{\alpha(1-\alpha)^2}\frac{\mu_L^*}{(1-\lambda)^2}\left[\frac{2\left(2+\alpha+\ln\Delta^{\frac{1+\alpha}{1-\alpha}}\right)}{(1-\theta)} + \Gamma\frac{\gamma}{\left(1+\mu_L^*\right)^3}\right],$$

where

$$\Gamma \equiv \left(3-\alpha^2\right)\mu_L^* - \left(1+4\alpha+\alpha^2\right) + \ln\Delta^{\frac{2\alpha\left[4\mu_L^*-\left(1+\mu_L^*\right)(1+\alpha)\right]}{1-\alpha}}.$$

A sufficient condition that ensures $f_{\alpha\lambda}(\lambda,\alpha,\gamma) < 0$ is $\Gamma > 0$, i.e.,

$$\left(3-\alpha^2\right)\mu_L^* + \ln\Delta^{\frac{2\alpha\left[4\mu_L^*-\left(1+\mu_L^*\right)(1+\alpha)\right]}{1-\alpha}} > 1+4\alpha+\alpha^2.$$

Since the left-hand-side is strictly increasing in Δ, a sufficient condition to ensure the above inequality is to evaluate it at $\Delta = 1$, which gives

$$\theta(1-\lambda)s > \frac{1+4\alpha+\alpha^2}{3-\alpha^2}.$$

Since the right-hand side above is strictly increasing in α, it is easy to check that the restrictions on parameters imposed at the beginning ensure this is always satisfied. Hence, we always have $f_{\alpha\lambda}(\lambda, \alpha, \gamma) < 0$, and an increase in banking complexity attenuates the effect of λ on the size of the unconstrained region. If $f_\lambda(\lambda, \alpha, \gamma) > 0$, this means that the contraction of the unconstrained region caused by a decrease in λ is smaller when banking complexity increases. If $f_\lambda(\lambda, \alpha, \gamma) < 0$, this means that the expansion of the unconstrained region caused by a decrease in λ is larger when banking complexity increases.