Banking on Experience *

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Abstract

Does bank experience reduce moral hazard in credit markets? Using U.S. corporate loan-level data, we find that, while experience with borrowers and co-lenders reinforces banks' monitoring incentives, sector experience dilutes them, calling for larger involvement in lending syndicates. In cross-sectional tests, we dissect scenarios in which specific forms of experience ameliorate lending outcomes. We interpret our findings through a loan syndication model in which all forms of experience ease monitoring, but sector experience raises asset liquidation values after loan defaults, diluting lenders' incentives to monitor. To attain identification, we exploit variation in experience at a point in time across firms, sectors, and co-lenders, and use bank mergers as instruments for the different forms of bank experience.

Keywords: Banks, Experience, Moral Hazard, Sector Specialization, Relationship Lending

JEL Classification: G21, D8

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1 Introduction

Traditionally, lenders acquire information about borrowers through screening and monitoring. They also learn by experience, that is, as a by-product of repeated interactions with borrowing firms, borrowers' peers, and other lenders. However, the way lender experience in credit markets interacts with the screening and monitoring of borrowers is far from obvious. Past experience provides a valuable stepping stone for monitoring activities, as it can enhance the productivity of monitoring and reduce the costs of acquiring information on borrowers. Nevertheless, experience could also make lenders "lazy": counting on knowledge previously accumulated in the credit market, lenders could have a natural incentive to shirk their costly monitoring duties. This fundamental trade-off is compounded by the multidimensional nature of credit market experience, as different types of experience on borrowers, borrowers' peers, or other lenders could differ significantly in the relative strength of the above forces.[1]

In this paper, we study different dimensions of learning by experience in credit markets and their implications for lending. While some of the mechanisms through which lenders accumulate information are institutionalized (e.g., information repositories such as credit bureaus and registers), credit market experience often is a by-product of lending activities and day-to-day interactions. We use the syndicated loan market as a testing ground for studying how credit market experience affects lending outcomes, firms' behavior, and banks' behavior vis-à-vis other syndicate members. Over the course of frequent and repeated interactions in lending consortia, syndicate members learn from the actions and decisions of other syndicate members, and they garner valuable experience on firms, sectors, and other banks acting as co-lenders. We then unpack lenders' experience into its multiple dimensions and study to what extent its various forms improve or worsen credit market outcomes.[2]

[1] The process of information acquisition entails other trade-offs. For example, lenders share information with borrowing firms, competing lenders, and borrowers' peers. They can then face a trade-off between the costly acquisition of information and the potential leakage of information to competing lenders. Further, an ample literature finds that information acquisition leads to hold-ups and rent-extraction issues (see Rajan, 1992; Degryse and Van Cayseele, 2000; Ioannidou and Ongena, 2010).

[2] As we elaborate below, the syndicated loan market allows to construct various measures of bank experience, but it also has limits. For example, syndicated loans are generally granted to relatively large firms, which tend to be less informationally opaque than smaller firms.

To address our research question, we use syndicated loan-level data on 20,932 loans from 663 banks to 5,309 non-financial firms. Our data span 64 industries (two-digit SIC) from 1987 to 2014.[3] We match syndicated loans with detailed data on the characteristics of firms and banks, as well as with information on regulatory actions against lead arrangers of the syndicated loans. Our data set allows us to construct three measures of bank experience. The first measure is $Firm - experience$ and is based on the number of times a bank has interacted with a firm in previous syndicates. We construct this measure by considering all the interactions of a bank (as a participant or as a lead arranger in a syndicate) with a firm and not solely the interactions as a lead arranger. This is important, as a participant bank may also learn about a borrower during its interactions in a lending consortium. The second measure is $Sector - experience$, which relies on the sector specialization a bank acquires through repeated interactions with borrowers operating in a specific sector (i.e., the importance of a sector for a bank). These two types of experience are often core components of relationship lending technologies (see, e.g., Boot and Thakor, 2000). The third measure, $Co - lending\ experience$, focuses on interactions among banks and consists of the number of previous interactions between the lead arranger and participants in syndicated deals. This measure captures the degree of learning from prior interactions with other banks over the course of syndicated loans.

We first ask our data whether banks in loan syndicates actively learn about borrowers, industries, and co-lenders over time (learning by participating). We find robust evidence of significant information spillovers in syndicated deals: the larger $Firm - experience$, the higher the likelihood that the lender will be a lead arranger in a future deal. Such a likelihood also increases in $Sector - experience$ and $Co - lending\ experience$ while controlling for a variety of loan, borrower, and bank characteristics.

We then investigate to what extent the different forms of prior experience attenuate or amplify moral-hazard issues in syndicated loans. The syndicated loan market features a distinct moral hazard problem in that lenders can have limited incentives to monitor borrowers. In the literature, the lead share is typically a proxy for the degree of moral

[3] We exclude loans classified as term loans B because banks hold none of these loans after the syndication. Term B loans are structured specifically for institutional investors and almost entirely sold off in the secondary market.

hazard in a syndicate: the larger the risk that the lead arranger shirks its costly due diligence and monitoring duties, the larger the loan share it should retain to raise its stake in the loan and, hence, its losses in case of inadequate monitoring (Sufi, 2007).

Our results suggest quite a nuanced impact of lender experience. Although prior $Firm-experience$ and $Co-lending\ experience$ reduce the need to concentrate a syndicated loan in the hands of the lead arranger, prior $Sector-experience$ increases the lead share. Thus, the estimates suggest that moral hazard within syndicates can be more severe when the lead arranger has higher sector experience. These results are obtained while controlling for credit supply and firm demand within an industry, and they are robust to potential endogeneity concerns related to banks' ability to manage their experience variables.

We rationalize these empirical findings through the lens of a theoretical model of loan syndication. In the model economy, lending banks accumulate experience on borrowing firms, co-lenders, and on the sector of activity of borrowers. Experience on borrowers and co-lenders facilitates syndicate arrangers' activity of loan monitoring. Experience on borrowers' sector of activity eases lenders' liquidation and redeployment of borrowers' assets among sector peers in the event of loan default. Exploiting their sector experience, in fact, lenders can more easily identify suitable asset buyers in the sector, and choose the most appropriate timing and location for asset liquidation. A lender with stronger sector experience will then manage to extract a larger value from asset liquidation after loan default. This, in turn, can dilute a lead arranger's incentive to properly monitor the loan. To counteract this effect and preserve the lead arranger's monitoring incentives, participant lenders demand that the lead arranger retains a higher loan share. Overall, the theoretical model suggests that, although all forms of experience naturally ease banks' role as monitors by reducing the cost of monitoring, they do not necessarily reduce the risk that banks shirk their monitoring tasks.

Building on the predictions of the theoretical model, we next perform a number of cross-sectional tests on sector, firm and bank characteristics to confirm that the baseline results reflect banks' accumulation of knowledge and information through experience, as well as to ascertain in what scenarios experience exerts a stronger influence. First, following

Rauch (1999) we exploit industry-level data on product complexity. In industries with high shares of differentiated products, the effects of sector experience can be more pronounced as there is larger uncertainty about product quality and trade costs (Caballero, Candelaria and Hale, 2018). In line with expectations, we find that the effects of $Sector - experience$ are more pronounced in industries characterized by high informational complexity of products. Second, we exploit information on banks' reliance on asset-based lending as well as information on asset market conditions. Consistent with the predictions of the theoretical model, the estimates suggest that the effect of a lender's sectorial experience is more pronounced when firms' assets are relatively more important in loan contracts (i.e., lending is asset-based rather than cash-flow based) and when asset markets feature higher heterogeneity in buyers' ability to repurchase assets.[4]

Third, we exploit heterogeneity in the composition of previous lending syndicates to ascertain the nature of $Co - lending\ experience$. We separate our measure of co-lending experience between the number of prior loans that involve banks lending to the same sectors and to different sectors. We find evidence that $Co - lending\ experience$ reflects primarily a common familiarity between banks that have previous experience in the same sectors. Finally, we exploit hand-collected information on regulatory enforcement actions against banks that are active in the syndicated market. Sanctions from regulators impose a reputational stigma on punished banks (Delis, Iosifidi, Kokas, Xefteris and Ongena, 2020). We find that participants that have experience with a punished lead arranger are more likely to step in and act themselves as lead arrangers. That is, experience enhances the flexibility with which banks can replace co-lenders hit by reputation shocks.

Overall, the results of the cross-sectional tests confirm the importance of the different forms of experience in the credit market. In particular, we detect a stronger effect of our measures of bank experience in scenarios in which we can plausibly expect information accumulated via past transactions to have a larger influence. These include sectors and products with higher information opacity, sectors with higher heterogeneity in asset liquidation values, as well as the aftermath of negative shocks to co-lenders' reputation.

[4] We also exploit firm-level heterogeneity using subsamples of firm informational opaqueness. The results suggest that the effects of lender experience are more pronounced for more informationally opaque firms.

Throughout the analysis, to control for unobserved factors and mitigate omitted-variable bias, we use the multilevel structure of our data set in a fashion similar to Jiménez, Ongena, Peydró and Saurina (2014, 2017). The multilevel structure of our data set allows for the inclusion of different types of granular fixed effects that help us isolate credit supply effects at the loan (bank-firm) level. We include bank-year and industry-year-firm rating category fixed effects to account for unobserved evolving credit supply effects and time-varying potential shifts in borrower demand within the same sector but in different rating categories, respectively (Acharya, Eisert, Eufinger and Hirsch, 2018). Also, we add firm fixed effects to control for time-invariant loan demand at the firm level because borrowers who choose lenders with higher levels of experience could have systematically different needs. In more restrictive specifications, we include bank-sector fixed effects to isolate the variation within the same bank-sector combination over time, thereby controlling for time-invariant portfolio-composition effects.

In addition, we mitigate any lingering concern that bank experience may be endogenous to the formation and structure of loan arrangements by exploiting changes in bank experience that stem from bank mergers. Following Garmaise and Moskowitz (2006) and Favara and Giannetti (2017), we focus on mergers between non-failing banks with assets of more than \$1bn.[5] To this end, we use hand-collected information on bank mergers where both banks are active in the syndicated loan market in the year before the merger. Specifically, we instrument a bank's $Firm$, $Sector$, $Co-lending-experience$ with information from the acquired (target) bank in the last quarter before the merger. We expect the experience of a target bank to reinforce the experience of the acquirer bank because knowledge is transferred through a merger. It is then reassuring that the instrumental variable estimates, which capture variation that is attributable to the acquired bank, support the causal interpretation of our findings.

Finally, our results survive several additional robustness tests. First, we show that they are robust to alternative definitions of the key variables of interest. Second, they are virtually unaltered when we drop loans in which the arranger is one of the largest three

[5] Garmaise and Moskowitz (2006) and Favara and Giannetti (2017) use the \$1bn threshold to identify mergers unrelated to local geographic conditions. This exogeneity argument seems plausible also when applied to the syndicated loan market (see for instance Giannetti and Saidi (2019a)).

U.S. banks, based on the number of deals in which banks participate. This enables us to verify that the findings are not driven by the efficiency of very large banks in originating large loan deals. Third, the results carry through if we exclude periods characterized by large aggregate shocks which could simultaneously affect banks' experience, such as the Global Financial Crisis.

Related literature. To the best of our knowledge, this paper is the first to focus exclusively on identifying how different dimensions of lender experience affect the corporate lending market. Our study speaks to different strands of the literature. First, we add value to the growing literature that studies the role of banks as information acquirers. Existing theories emphasize the role of banks in producing soft information via screening (Diamond, 1991) and monitoring (Rajan and Winton, 1995). There is also substantial evidence that banks gather private information about their borrowers over multiple interactions (Boot, 2000; Ongena and Smith, 2000; Gopalan, Udell and Yerramilli, 2011; Berger, Minnis and Sutherland, 2017). Surprisingly, there is instead little evidence on how this information is used in future transactions not only with the same firm, but also with other firms in the same industry and with co-lenders in loan syndicates. Our analysis yields insights on how lenders employ valuable experience with borrowers and co-lenders.

Works that study soft information in lending include Agarwal and Hauswald (2010), Iyer, Khwaja, Luttmer and Shue (2016), Schwert (2018), Liberti and Petersen (2019), and Darmouni (2020). Botsch and Vanasco (2019) use syndicated loan data and define the "learning by lending" practice a potential substitute for banking relationships. In particular, they provide evidence that banks collect information about borrowers as relationships develop. By investigating the multiple dimensions of lender experience and studying the role of sector and co-lender experience, we find evidence that bank experience can have ambiguous consequences for the extent of moral hazard in lending. In particular, we show that it is critical to capture the different angles of the accumulation of bank experience, including sectorial experience, to sort out the ultimate impact on credit market outcomes.[6] To be clear, the key role that sectorial knowledge plays in commercial lending decisions has

[6] In our analysis, we also analyze nonpricing characteristics that can better connect to the value that additional information generates (Roberts and Sufi, 2009).

been recognized by scholarly studies and more broadly by the banking community. Indeed, banks often conduct in-house industry analyses as part of loan underwriting. In empirical studies, industry knowledge is often captured through the inclusion of industry fixed effects, whose estimated magnitude generally turns out to be quite large. For example, Bushman, Gao, Martin and Pacelli (2021) show that bank fixed effects add little incremental explanatory power for loan terms, covenants, or loan performance, while when bank fixed effects are replaced with bank-industry or bank-time fixed effects to allow for bank specialization or changing circumstances over time, both sets of fixed effects significantly increase the incremental explanatory power of banks.[7]

Our study also contributes an econometric approach to identifying experience-based learning using information gathering and sharing in lending consortia. Although several papers focus on identifying sector- or firm-specific characteristics that matter for the acquisition of information in a continuing relationship, we construct three measures of bank experience. On a broader level, we separate learning by experience from size, network, and time effects. To this end, we mainly use variation within bank-year as a source of identification to minimize omitted-variable bias concerns. Specifically, we observe the same bank repeatedly and compare its decision-making over time across firms, industries, and other banks. In addition, following Favara and Giannetti (2017), we utilize bank mergers to identify exogenous shocks to bank experience and alleviate simultaneity bias concerns.

The remainder of the paper unfolds as follows. In section 2, we lay out testable hypotheses on the effects of lender experience through a theoretical model of syndicate loan participation. Section 3 provides details on the empirical methodology, and section 4 presents the data and the approach that we use to measure the variables of interest. Section 5 contains the main results. Section 6 presents further tests that dissect the scenarios in which bank experience has stronger influence. Section 7 contains robustness tests and studies implications of bank experience for firm outcomes. Section 8 concludes. Proofs of the model and additional empirical results are relegated to the online appendix.

[7] Saunders (1994) discusses the role of bank loan concentration in industries with reference to oil and gas loans in Texas.

2 Theoretical Model and Testable Predictions

In what follows, we derive testable hypotheses on how bank experience affects the extensive margin of syndicated loans (decision to be the lead arranger of a syndicated loan) and their intensive margin (share of loan the lead arranger retains). While the predictions about the impact on the extensive margin turn out to be more clear-cut, the predicted impact of past experience on the intensive margin of syndicates is ambiguous a priori. As we show below, in fact, the accumulation of experience tends to moderate or, in some circumstances, accentuate moral hazard between lead arrangers and participants. Depending on this effect, the lead arranger may have to retain a smaller or larger share of the loan to commit to monitoring the loan on behalf of the participants.

The type of lender experience turns out to be critical for determining the sign of the effect. The intuition for the possibly different effects of bank experience consists of the different ways in which bank experience exerts a role in the model economy. While a lead bank experience on the borrower and the co-lenders naturally eases the activity of monitoring of the lead bank, incentivizing its monitoring, the sectorial experience of a lead bank facilitates the extraction of value from the repossession and resale of the borrower's assets in the event of borrower default, diluting the lead bank's incentive to monitor. Therefore, as we will see below, these different channels of influence of the types of bank experience have sharply different consequences for banks' incentive to monitor and for the structure of syndicated loans.

2.1 Model Set-up

Agents, technologies and markets Consider a model economy populated by a unit continuum of firms and a larger continuum of deep-pocketed lenders (banks). Firms start with no endowment but have project investment opportunities. Each firm has the opportunity to invest in an indivisible project. A project requires an investment of final good of size one at the beginning of the period. At the end of the period the project succeeds with probability μ and yields an output $Y > 1$ of final good. With the complementary probability $1 - \mu$ the project fails and yields no output but the assets of the project, for an amount $A < 1$, can be resold in an asset liquidation market and reused by other firms.

We model the redeployment of assets in a parsimonious way. Any active firm can purchase liquidated assets and reuse them in a simple scrap technology obtaining an output y_i of final good per unit of assets reused. We allow for heterogeneity in the productivity of the scrap technology across the possible reusers of assets (Shleifer and Vishny, 1992; Habib and Johnsen, 1999). In particular, we posit that there are two "regions" (or "locations" or "sub-industries") characterized by a different productivity of liquidated assets. To fix ideas, we label the two sub-markets as "high" and "low" henceforth. Within each sub-market, firms feature idiosyncratic productivity in the reuse of liquidated assets (more details below).

Financing Firms have no initial endowment and, hence, need to obtain financing from lenders to implement projects.[8] Lenders have no project opportunities but are each endowed with at least one unit of final good. In addition to financing entrepreneurs, lenders can invest their funds at a market gross interest rate normalized to one.

Each firm can approach a group of lenders in the economy to obtain a syndicated loan. In a syndicate, one of the lenders will act as the lead arranger, managing the loan and actively monitoring the borrower, while the other lenders will act as co-financiers or syndicate participants. A syndicated loan contract specifies the loan to be extended at the onset of the period, a fixed fee χ to be paid by the borrower to the lead arranger for his loan arrangement activity, a total repayment R to the pool of lenders in case of project success and loan repayment, as well as the right of the lenders to repossess the assets of the borrowing firm in the event of project failure. We denote by α the share of a loan retained by the lead lender and correspondingly by $1 - \alpha$ the share of the loan co-financed by the participant lenders. The lead lender and the participants will share the repayment R in case of project success in proportion of their loan shares. Hence, in case of project success the repayment to the lead lender is given by αR, and the repayment to the syndicate participants is $(1 - \alpha)R$. Moreover, in case of loan default and liquidation the lenders will

[8] We could assume some positive initial endowment without changes in the results. Observe that, for simplicity, we posit that financing is instead not needed to purchase liquidated assets and reuse them. Put differently, the scrap liquidation technology yields output instantaneously.

be able to repossess assets in proportion of their loan shares, obtaining αA and $(1-\alpha)A$, respectively.

By monitoring the borrowing firm, a lead arranger can induce the borrower to exert more effort in the project, raising the project success probability. Precisely, we let the success probability, μ, of a project be equal to the monitoring effort of the lead arranger. The lead arranger sustains an effort cost for monitoring the borrower which is convex in his monitoring level, $\frac{c\mu^2}{2}$. As it is typically the case, loan contracts cannot be contingent on the monitoring level, as this is not verifiable by third parties such as courts. As noted, we posit that the past experience (Ω) accumulated by the lead arranger with the borrower and with the co-lenders enters as an input in monitoring activities, reducing the cost of monitoring. Formally, $c = c(\Omega)$ with $c'(.) < 0$.

Liquidation In the event of project failure and loan default, each lender can resell the assets he repossessed in the liquidation market. In Section 2.5.1 we will show the robustness of the results to considering a scenario in which participant lenders delegate the lead lender to liquidate all the repossessed assets after default.[9] We posit that the potential reusers of assets are equally allocated to the "high" and "low" markets. The output obtained in the high market by a firm that purchases one unit of liquidated assets is distributed uniformly over the $[\overline{L}-\eta, \overline{L}]$ support

$$y_i \sim U[\overline{L}-\eta, \overline{L}]. \tag{1}$$

Similarly, the output obtained in the low market by a firm that purchases one unit of liquidated assets is distributed uniformly over the $[\underline{L}-\eta, \underline{L}]$ support

$$y_i \sim U[\underline{L}-\eta, \underline{L}], \tag{2}$$

where $\underline{L} < \overline{L} < 1/A$. The value of $L \in \{\overline{L}, \underline{L}\}$ in a market is not perfectly observable. However, a lender observes an imperfect signal about it. The precision of this signal will depend on the past experience accumulated by the lender in the sector. For example,

[9] The banking industry and practitioners' studies debate extensively the techniques and procedures for the management and liquidation of recovered assets and the value of banks' sectorial knowledge for a more efficient asset liquidation. See, e.g., Cavalli and Sumper (2015).

sectorial experience will enable a lender to tease out the characteristics of the potential asset buyers, understand where the best buyers are located, and more in general better understand the asset market conditions. Shleifer and Vishny (1992) and Diamond and Rajan (2002), for example, show that the resale value of project assets in the event of borrower default increases with the lender's prior knowledge of the redeployability of the assets among sector peers.

We denote by π the past experience accumulated by a lead lender in the sector and also the informativeness of the signal the lead lender observes about the value of L in the two sub-markets. Precisely, a lead lender with sectorial experience π will be able to identify the high market ($L = \overline{L}$) with probability $\pi > 1/2$. We will later micro-found the link between the precision of a lender's signal and the lender's sectorial experience. Without loss of generality we normalize to $\pi_p = 1/2$ the sectorial experience of the participants (see Appendix A.6 for a generalized case with π_p different from 1/2).

Additional features As in Ivashina (2009), lenders feature risk aversion associated with their involvement in loan syndicates. We model this in reduced form by positing that the outside option of a lender entails a risk premium $\phi(\alpha)$ that is increasing in the share the lender retains in the loan, that is, $\phi'(.) > 0$, with $\phi(0) = 0$.

Keeping track of the model Figure 1 is based on Ivashina (2009) and helps illustrate the setting. The participant-demand curve represents the lead share demand of syndicate participants, meant as the lead share α that induces lenders to participate in a loan for a given repayment R. The lead-supply curve represents the share under which a bank is willing to act as a lead arranger, for a given repayment R. The properties (slope and position) of the demand and supply curves will be derived and discussed below.

2.2 Model Solution

We solve for the equilibrium of the model by backward induction. We first solve for the equilibrium in the asset liquidation market, for given monitoring decisions of lead lenders and contract choice decisions in the syndicated loan market. Then, we solve for the monitoring chosen by lead lenders. Finally, we solve for the contract terms in syndicated loans.

Liquidation market Using the distribution of liquidation returns in (1) and (2), and denoting by M the measure of active firms in the economy, in the high market and in the low market the demand for liquidated assets is respectively given by

$$D^H = \frac{M(\overline{L} - p_H)}{2\eta}; \quad D^L = \frac{M(\underline{L} - p_L)}{2\eta}. \tag{3}$$

The supply of liquidated assets in the high market in turn reads

$$S^H = \frac{M}{2}(1-\alpha)(1-\mu)A + \pi M\alpha(1-\mu)A, \tag{4}$$

that is, it equals the supply of liquidated assets by participant lenders $(M/2)$(1-α)(1-μ)A plus the asset supply of lead lenders $\pi M\alpha(1-\mu)A$.[10] The asset supply in the high market is decreasing in the monitoring level of lead lenders μ (more monitoring will imply fewer project failures and, hence, fewer asset liquidations) and increasing in their sectorial experience π. In fact, lead lenders will exploit their sectorial experience to chase the higher returns from asset liquidation that can be obtained in the high market.

By the same logic, in the low market the supply of liquidated assets equals[11]

$$S^L = \frac{M}{2}(1-\alpha)(1-\mu)A + (1-\pi)M\alpha(1-\mu)A. \tag{5}$$

Solving for the asset resale price in the two sub-markets, we obtain

$$p_H = \overline{L} - \eta(1-\mu)A\left[(1-\alpha) + 2\pi\alpha\right] \tag{6}$$

and

$$p_L = \underline{L} - \eta(1-\mu)A\left[(1-\alpha) + 2(1-\pi)\alpha\right]. \tag{7}$$

[10] As it will become clear below, in equilibrium the chosen values of μ and α are equal across all syndicated loans.

[11] Observe that for a lender it is equivalent to randomize on the sub-market where to sell assets or split the asset sale between the two sub-markets.

The expression in (6) implies that the asset resale price p_H in the high market is weakly increasing in μ and decreasing in π and α (and strictly so when $\eta > 0$). On the other hand, from (7), the asset resale price p_L in the low market is weakly increasing in μ, π and α.

Using (6) and (7), and recalling the signal observed by lenders, we obtain the revenue per unit of assets (p_{lead}) that a lead lender expects to obtain in the asset liquidation market:

$$p_{lead} = \pi p_H + (1-\pi)p_L = \widetilde{L} - \eta(1-\mu)A\left\{(1-\alpha) + 2\alpha\left[\pi^2 + (1-\pi)^2\right]\right\} \tag{8}$$

where $\widetilde{L} \equiv \pi\overline{L} + (1-\pi)\underline{L}$. This asset liquidation value is increasing in monitoring μ and decreasing in α. $\widetilde{L}$ is also increasing in sectorial experience π as long as

$$\frac{\partial p_{lead}}{\partial \pi} = (\overline{L} - \underline{L}) - 8\eta\alpha(1-\mu)A(\pi - \frac{1}{2}) > 0 \Leftrightarrow \eta < \frac{\overline{L} - \underline{L}}{8\alpha(1-\mu)A(\pi - \frac{1}{2})}, \tag{9}$$

which we assume henceforth. Intuitively, the direct benefit that sectorial experience has in guiding lead arrangers to a more efficient asset liquidation (i.e., the choice of the high market) should not be outweighed by the price drop induced by the concentration of asset sales in the high market.[12]

Monitoring We now study the monitoring choice of a lead lender. A lead lender solves

$$\max_{\mu}\left\{\alpha\mu R + \alpha(1-\mu)p_{lead}A - \frac{c(\Omega)\mu^2}{2} - \phi(\alpha) + \chi\right\}, \tag{10}$$

from which we obtain the first order condition

$$\alpha\left(R - p_{lead}A\right) - c(\Omega)\mu = 0. \tag{11}$$

The equilibrium monitoring level of a lead lender μ can be solved by combining the first order condition (11) and the definition of p_{lead}. We can show (see Appendix A.1) that it is increasing in the loan share a lead lender retains, α, decreasing in the level of his sectorial

[12] The condition is satisfied more easily when the elasticity η of demand in a market is not excessively high, as otherwise the concentration of asset sales in the high market will have a large depressing effect on the asset price. It is also satisfied more easily when the two sub-markets feature a sufficiently large gap in the position of the asset demand, that is, $\overline{L} - \underline{L}$ is not too small.

experience, π, and increasing in the level of his experience Ω about the borrower and the co-lenders. Intuitively, sectorial experience will raise a lead lender's expected asset liquidation value in case of default, diluting his incentive to monitor. On the other hand, borrower and co-lender experience will reduce the cost of monitoring, boosting his monitoring incentive.

Demand of lead share by participant lenders. We can now derive the demand of lead shares by participant lenders in loan syndicates. Denote by p_{par} the revenue per unit of assets (p_{par}) that a participant lender expects to obtain in the asset liquidation market. Participants' zero-profit constraint reads

$$(1-\alpha)\mu R + (1-\alpha)(1-\mu)p_{par}A = (1-\alpha) \tag{12}$$

where the revenue expected by participant lenders per unit of assets sold in the asset liquidation market satisfies

$$p_{par} = \frac{1}{2}p_H + \frac{1}{2}p_L = \frac{1}{2}(\overline{L} + \underline{L}) - \eta(1-\mu)A. \tag{13}$$

Interestingly, this expected liquidation value of participants does not depend on α or π independently, but only through the monitoring level of the lead lender μ.[13]

We can show (see Appendix A.2) that the demand schedule of participants is downward sloping, that is, participants request a lead lender to retain a lower lead share α when the repayment R is larger. Moreover, the demand schedule shifts outward when lead lenders' sectorial experience π rises, while it shifts inward when lead lenders' experience Ω about the borrower and the co-lenders increases. Intuitively, as noted above, sectorial experience can make a lead arranger "lazy" by raising his expected liquidation value in case of a borrower's default. In this case, it is necessary to concentrate the loan more in order to overcome the lead arranger's incentive to shirk its monitoring duties. On the other hand, borrower and co-lender experience can make it cheaper for a lead arranger to monitor the

[13]Intuitively, a higher experience of lead arrangers will imply a larger asset supply in the high market, reducing the price that can be fetched by participant lenders in that market. On the other hand, it will correspondingly reduce the asset supply in the low market, raising the price that can be fetched by participant lenders in the low market. The two effects cancel out when $\pi_p = \frac{1}{2}$. In Appendix A.6, we also consider $\pi_p > \frac{1}{2}$.

borrower, as captured by a lower marginal cost of monitoring (c). This makes it easier for syndicate participants to induce the lead arranger to choose a certain monitoring level. Thus, we expect that participants request the lead arranger to retain a lower share of the loan for given repayment R.

Supply of lead share by lead lenders. Let us now turn to studying the supply of lead share by lead lenders. The participation constraint of a lead lender reads[14]

$$U = \alpha\mu R + \alpha(1-\mu)p_{lead}A - \frac{c(\Omega)\mu^2}{2} - \phi(\alpha) + \chi = 0. \tag{14}$$

In Appendix A.3, we show that the supply curve is upward sloping under moderate parameter restrictions. That is, lead lenders are willing to retain a higher share α when the repayment R is larger. Moreover, the supply schedule shifts outward when lead lenders' sectorial experience π increases and when their borrower and co-lender experience Ω rises.

2.3 Intensive Margin

We can now study the implications of the model for the role of lenders' experience.

1) *Substitutability between lead arranger's share and experience.* Past experience about the borrower and the co-lenders can make it cheaper for a lead arranger to monitor the borrower. In the model this is captured by a lower marginal cost of monitoring (c). This makes it easier for syndicate participants to induce a lead arranger to choose a certain monitoring level: in Figure 1, the participants' demand for the lead arranger's share shifts inward. Therefore, the model implies that an increase in past experience about borrower and co-lenders tends to lead to a lower required minimum share α for a lead arranger. That is, we have a mechanism of substitutability between the lead arranger's share and his past experience.

2) *Complementarity between lead arranger's share and sectorial experience.* A case of complementarity can arise if past sectorial experience exacerbates the risk of opportunistic behavior of lead arrangers. Specifically, past sectorial experience can make the lead ar-

[14] Recall that a lead lender's expected return includes a fixed fee χ paid by the borrower from income generated by the project or personal income.

ranger “lazy” by raising his expected asset liquidation value in case of a borrower’s default. In this case, it is necessary to concentrate the loan more in order to overcome the lead arranger’s incentive to shirk its monitoring duties: in Figure 1, the demand of participants shifts outward when lead lenders’ sectorial experience rises. Therefore, the model implies that an increase in past sectorial experience tends to lead to a higher required minimum share α for a lead arranger. That is, we have a mechanism of complementarity between the lead arranger’s share and his past experience.

Additionally, an increase of the lead arranger’s sectorial experience π or a reduction in the monitoring cost $c(\Omega)$ induced by higher borrower and co-lender experience reduce the repayment requested for any lead share, shifting the supply curve outward.

Testable Hypothesis 1: The predicted impact of bank experience on lead shares is ambiguous a priori, and depends on the type of experience:
i) A lower lead share is more likely when banks’ experience about borrowers and co-lenders eases monitoring activities;
ii) A higher lead share occurs when banks’ sectorial experience boosts banks’ expected asset liquidation values in the event of borrowers’ default.

As noted, in the empirical analysis we will study the effect of experience on borrowers, banks, and borrowers’ sector of activity on the loan share retained by lead arrangers in syndicates (which captures the extent of moral hazard within syndicates).

2.4 Extensive Margin

Having studied the effects of lenders’ experience on the concentration of syndicated deals, we examine its effect on the likelihood that a syndicated loan is granted. With χ denoting the arrangement fee paid by a borrower and Y denoting the borrower’s output in case of project success, we have that a borrower will be willing to take a loan and implement a project as long as

$$Y\mu \geq R\mu \ + \chi. \tag{15}$$

Let $F(Y)$ denote the probability that a borrower's return Y does not satisfy the above (weak) inequality.[15] Consider first the effect of borrower and co-lender experience through the cost of monitoring c. It is evident that

$$\frac{\partial F(R + \frac{\chi}{\mu})}{\partial c} \geq 0. \tag{16}$$

In Figure 1, in fact, the demand curve shifts inward, and the supply curve shifts outward when, thanks to borrower and co-lender experience, the cost of monitoring is lower, reducing the repayment requested from the borrower (thus, $\frac{\partial R}{\partial c}$ is strictly negative). Moreover, μ will increase if the cost of monitoring c is lower, reducing the term $\frac{\chi}{\mu}$. On the other hand, the likelihood of making a loan is ambiguously related to the sectorial experience π of the lead arranger. In Figure 1, in fact, both the demand curve and the supply curve shift outward when π is higher (thus, $\frac{\partial R}{\partial \pi}$ is ambiguous ex ante). Moreover, μ will drop when π is higher, increasing the term $\frac{\chi}{\mu}$.

Testable Hypothesis 2: When bank experience about borrower and co-lenders eases monitoring, the likelihood that the bank acts as a lead arranger (weakly) increases. If, instead, sectorial experience increases the bank's expected liquidation value, its predicted impact on the probability that the bank acts as a lead arranger is ambiguous.

2.5 Robustness, Extensions, and Welfare

In what follows we study robustness and extensions of the model. Proofs and details are relegated to the Appendix.

2.5.1 Robustness: delegated liquidation

The reader could wonder how the results would be affected if, after borrowers' default, participant lenders could (partially) delegate lenders for performing asset redeployment on their behalf. The scope for such delegated liquidation can vary across settings, but it is nonetheless useful to consider this possibility in our framework. We could think that lead and participant lenders engage in an ex-post bargaining process over the rent associated

[15] Thus, the measure of active firms in the economy will be $M = 1 - F(R + \frac{\chi}{\mu})$.

with lead lenders' higher liquidation skills. It is immediate to show that as long as lead lenders can appropriate a not too small share of the surplus associated with their higher liquidation skills, all the results of the baseline set up would carry through. Appendix A.4 provides full details on this robustness analysis.

2.5.2 More on the role of lenders' experience

In this extension, we elaborate on the role of lenders' experience. A first observation regards the possibility of micro-founding lenders' sectorial experience π through a simple learning process. We provide an example here. Suppose that $\underline{L} > \overline{L} - \eta$, that is, the supports of productivities in the two sub-markets for asset liquidation have overlaps. Consider a lender who randomly selects a sub-market to engage with and who, over the course of his lending interaction with each borrower, gains knowledge about that borrower's ability to reuse assets (i.e., about the value of that borrower's y_i). We can show that in N periods (or after N rounds of lending to different borrowers), the probability that the lender is able to discern the type of the market (the value of L) will be

$$\pi = 1 - \left[\frac{\eta - (\overline{L} - \underline{L})}{\eta}\right]^N \tag{17}$$

which is increasing in N (i.e., in the sectorial experience matured by the lender).

A further observation regards the influence of information complexity on the role of lenders' experience. The baseline set up can be augmented by allowing the informativeness of the signal observed by a lender to be increasing in the informational complexity of the firm's assets (product). Put differently, the more the assets are informationally complex, the greater the added value of the signal observed by a lender. In particular, we can posit that the probability that a lead lender observes a more informative signal thanks to his sectorial experience is given by $\lambda\pi$, where λ measures the degree of informational complexity of the assets. It is immediate that the effects of lenders' sectorial experience obtained above will be larger the higher the value of λ (see Appendix A.5 for details).

Testable Hypothesis 3. A larger informational complexity of products tends to reinforce the effects of banks' sectorial experience on loan contract terms.

2.5.3 Lending technologies

In this second extension, we elaborate on the influence of lending technologies. A distinct feature of loan contracts consists of their reliance on cash-flow based lending or asset-based lending. We extend our main set up to gain insights into the influence of such lending technologies on the role of lenders' experience. We do so in two ways. We first study how a larger incidence of asset-based lending can affect the impact of experience on loan contracts. In particular, we investigate the effects of changes in the parameter A, which in the baseline model can capture the relative importance of pledgeable assets in project loans. In Appendix A.7, we instead modify our setting to allow for the coexistence of two types of borrowing firms in the economy: a group of firms more reliant on cash-flow based lending (lower A relative to Y) and a group of firms more reliant on asset-based lending (higher A relative to Y).

When studying the influence of asset-based lending, two forces contrast with each other. On the one hand, a larger value of - and larger reliance on - pledgeable assets magnifies the effect of sectorial experience on the liquidation value expected by lead lenders in case of loan default. This, in turn, exacerbates the dilution of lead lenders' monitoring incentives, calling for a larger lead lender share α to preserve monitoring incentives. On the other hand, a larger value of pledgeable assets raises the return expected by participant lenders in the event of default, thereby reducing the need to incentivize lead lenders' monitoring through a higher lead share α. The statement below summarizes our result with respect to the influence of lending technologies. In the statement, larger reliance on asset-based lending refers to a higher value of A.

Testable Hypothesis 4. As long as reusers' heterogeneity in the asset liquidation market is not too large (i.e., in the two sub-markets η is not too high) and the monitoring cost c is not too large, a relatively larger reliance on asset-based lending (higher A) reinforces the effects of lenders' sectorial experience on loan contract terms.

2.5.4 Welfare

While the objective of our analysis is primarily positive, it is useful to investigate the welfare properties of our equilibrium and learn insights into the welfare consequences of lenders' experience. Since we will not be able to test welfare implications with our data, a reader may directly move to the empirical analysis without loss of continuity.

In Appendix A.8 we study the problem of a constrained policy maker who aims at maximizing the total combined welfare of borrowers and lenders and who can affect lenders' monitoring choice μ. In line with prior studies, the policy maker takes as given the determination of the equilibrium in the asset liquidation market and in the syndicated loan market (thus, for given monitoring μ, he takes as given the choices of α and R). We posit that the policy maker can implement the desired optimal monitoring level μ_P by imposing a tax or giving a transfer to lenders in case of asset liquidation (in fact, this will affect lead lenders' monitoring choice).

Let V denote the average productivity of liquidated assets. By comparing the optimal monitoring induced by the policy maker, μ_P, with the decentralized equilibrium one, μ, we find that the former exceeds the latter (i.e., there is under-monitoring in equilibrium) if [16]

$$\mu_P - \mu = \frac{\overbrace{-c\alpha[(V - p_{lead})A - (Y - R)]}^{W_1 \gtrless 0} + \overbrace{c(1-\alpha)(Y - VA)}^{W_2 > 0} + \overbrace{\frac{\partial V}{\partial \mu}\left[c - \alpha\left(R - p_{lead}A\right)\right]A}^{W_3 > 0}}{\underbrace{c\left(c + \frac{\partial V}{\partial \mu}A\right)}_{>0}} > 0. \tag{18}$$

The monitoring level targeted by the policy maker tends to be larger than the decentralized one for two reasons. The policy maker accounts for the return of all the lenders and borrowers, not only of the lead lenders (term W_2 in the numerator of the right hand side of (18)). The policy maker also accounts for the fact that, if monitoring is higher, there will be fewer assets liquidated and the average productivity V of liquidated assets will be higher (this pecuniary externality is captured by the term W_3 in the numerator). A third

[16] Note that, in deriving equation (18), we focus on a scenario with a degenerate distribution $F(Y)$ of firms' output over the relevant region.

force is ambiguous. The policy maker accounts for the fact that liquidated assets may have an average productivity, V, larger than the resale price expected by lead lenders, p_{lead}. Hence, in this dimension the policy maker may tend to choose lower monitoring than what is implied by the decentralized equilibrium, which dilutes the incentive to target a high monitoring level. This is captured by the term W_1 in the numerator.

The above implies that in the model economy lead lenders' monitoring can be sub-optimally low in equilibrium ($\mu_P - \mu > 0$) but, in some circumstances, it could also be suboptimally high ($\mu_P - \mu < 0$). This also yields insights for the welfare consequences of lenders' sectorial experience. In fact, if lenders' monitoring is suboptimally low in equilibrium, lenders' sectorial experience will have an ambiguous effect on welfare. On the one hand, it will depress welfare by further reducing monitoring below its optimal level. On the other hand, it will boost welfare by raising the average productivity of assets in the liquidation market (that is, by improving the liquidation value of the assets of defaulted projects through more efficient liquidations). If lenders' monitoring is instead suboptimally high in equilbrium ($\mu_P - \mu < 0$), lenders' sectorial experience will certainly boost welfare both by pushing monitoring downward, towards its optimal level, and by raising the average productivity of liquidated assets.

We develop a numerical example in Appendix A.8. We find that, under a wide range of parameters, the equilibrium level of monitoring is lower than that chosen by a policy maker. In the numerical example, while depressing monitoring below the optimal level, lenders' experience nonetheless exerts an overall positive effect on total welfare by significantly raising the average productivity of liquidated assets.

3 Empirical Methodology

We test the implications of the model using data on loans originated in the U.S. syndicated corporate loan market, matched with comprehensive firm and bank data. Based on our hypotheses in section 2, we estimate two main empirical models.

First, we examine how experience influences a bank's decision to act as a lead arranger (extensive margin). This is formulated as a linear probability model of the following form:

$$Prob(lead_{b,f,s,t}) = \alpha' + \lambda_1 * Sector^{Exper}_{b,s,t} + \lambda_2 * Firm^{Exper}_{b,f,t} + \lambda_3 * Co-lending^{Exper}_{b,t} + \beta_1 * L_{l,t} + \beta_2 * F_{f,t-1} + \epsilon_{b,f,s,t} \quad (19)$$

where *Lead* equals one when bank b is defined as a '*lead arranger credit*' of a loan to firm f in sector s at time t, and zero otherwise (Bharath, Dahiya, Saunders and Srinivasan, 2011).[17] The sample set for equation (19) includes all banks that have been active at least once as a lead arranger in our sample in the last five years up to the date that the loan is granted. The timing of the variables is in line with the idea that a firm with certain characteristics at time $t-1$ will seek a loan at time t. The main independent variables are the $Sector$, $Firm$, and $Co-lending$ experience, and their coefficients (λ_1, λ_2, and λ_3) reflect the change in the propensity to act as a lead arranger. α' denotes different levels of time-invariant and time varying fixed effects (more details later on). L and F are several loan and firm control variables, while ϵ is a loan-level idiosyncratic disturbance.

Second, we analyze the impact of experience on the retained share conditional on being a lead arranger (intensive margin). We estimate the following model:

$$Lead\ lender\ share(\%)_{b,f,s,t} = \alpha' + \lambda_1 * Sector^{Exper}_{b,s,t} + \lambda_2 * Firm^{Exper}_{b,f,t} + \lambda_3 * Co-lending^{Exper}_{b,t} + \beta_1 * L_{l,t} + \beta_2 * F_{f,t-1} + \epsilon_{b,f,s,t} \quad (20)$$

where *Lead lender share*(%) represents the share (in percentage) that lead bank b retains in a syndicated loan to firm f in sector s at time t.

An identification challenge in the empirical models is the potential bias of λ_1, λ_2, and λ_3 due to unobservable characteristics related to the bank, firm, or industry that also explain variation in lead propensity and the *Lead lender share*(%). However, our loan-level granularity helps us overcome this issue through the inclusion of several detailed fixed effects. In the above empirical models, we include bank-year and industry-year-firm rating

[17]We choose a linear probability approach for computational ease, but the results are robust to using a Probit model.

category fixed effects to isolate simultaneous changes in credit supply and firm demand within an industry (Jiménez, Ongena, Peydró and Saurina, 2014; Giannetti and Saidi, 2019a).[18] These fixed effects control for time-varying unobservable bank fundamentals (such as profitability, management policies, monetary condition, and other balance sheet characteristics), firm risk fundamentals (e.g., future prospects, forecast analyst, profitability), as well as banks' shifting to firms with different ratings within the same industry. In addition, we add firm fixed effects in our robustness analysis to control for firm-level loan demand that remains constant over time. In some more restrictive specifications, we further include bank-industry fixed effects to isolate the variation within the same bank-industry combination over time, thereby controlling for time invariant portfolio-composition effects.

Fixed effects account for omitted factors, but to further address any lingering endogeneity concerns that bank experience may be endogenous to the formation and structure of loan arrangements, we conduct an instrumental variables (IV) estimation in section 5.2. Specifically, we exploit M&A between non-failing banks with assets more than $1bn that are active in the syndicated market as a plausibly exogenous shock (Garmaise and Moskowitz, 2006; Favara and Giannetti, 2017). We construct instruments for sector, firm, and co-lending experience using only the historical experience variables of the target (acquired) bank. Our instruments are defined within a year, starting when a merger occurs and extending until the new loan origination. The instruments equal zero before the merger.

4 Data and Measurement

4.1 Data Sources

To test our hypotheses, we need loan-level data for firms in a wide range of industries as well as comprehensive information on banks' interactions with firms and co-lenders. Our analysis is based on a matched bank-firm data set containing corporate loans that were originated in the United States. We construct our data set using six data sources: Thomson Reuters LPCs DealScan database, the Call Reports of the Federal Reserve Board of

[18] *Firm rating category* is an indicator variable for investment grade, non-investment grade and unrated firms.

Governors (FRB), Compustat, hand-collected data on enforcement actions by the three main U.S. banking supervisory authorities (FDIC, OCC and FED), Rauch (1999) classification on product complexity and data on the comovement of firms' value added within industries from Guiso and Minetti (2010).

We begin with a brief description of the syndicated corporate loan market, as a number of studies analyzed this market (see, e.g., Sufi, 2007, among others). The main advantage of studying the syndicated market is that a group of banks co-finance a single borrower, and banks' overlapping portfolios allow us to measure different levels of experience among syndicate members.[19] In the past two decades, syndicated lending has amounted to about half of the total commercial and industrial (C&I) lending and therefore it is often used to assess bank lending policies (Ivashina and Scharfstein, 2010).

In general, the syndication process works as follows. The borrowing firm signs a loan agreement with the lead arranger, which specifies the loan characteristics (collateral, loan amount, covenants, a range for the interest rate, etc.). The members of the syndicate are categorized into three groups: the lead arranger (or co-leads, if more than one), the agents (or co-agents), and the participant lenders. The first group consists of senior syndicate members and is led by one or more lenders, typically acting as mandated arrangers, arrangers, lead managers, or agents. Lead arrangers coordinate the documentation process, choose whom to invite to participate in the loan syndicate, and may delegate certain tasks to the co-agents or participants. In addition, the lead arranger receives a fee from the borrower for arranging and managing the syndicated loan.

We obtain data on syndicated loans at origination from the Thomson Reuters Dealscan database. This database provides detailed information on loan characteristics like amount, borrowing spread, maturity, collateral, performance pricing provisions, and covenants, among others. DealScan does not contain complete information on lenders' shares for

[19] As noted, a limit of syndicate loan data is that they tend to cover relatively large firms. In studying how banks' industry expertise influences banks' information acquisition, Berger et al. (2017) use Risk Management Association (RMA) data, which tend to cover relatively small businesses. While the RMA data set provides a rich aggregation of financial statements from participating member banks, it is less comprehensive in providing granular, firm-level data and lacks information on bank-to-bank interactions. Its format, although useful for trend analysis across different scales of businesses and regions, does not accommodate an in-depth investigation of specific firm- and-co-lending experiences. For this reason, we have chosen to work with syndicated loan market data, as they better suit our research focus.

all loans. For the loans with a full breakdown of shares, we allocate the exact loan portions to the individual lenders. For the remaining loans, we follow Giannetti and Laeven (2012) and De Haas and Van Horen (2013) and divide the loan volumes among the missing syndicate members on a pro-rata basis. Importantly, we also use alternative rules like keeping only a subsample of loans with complete information or estimating a model in which the loan shares of individual lenders is the dependent variable and obtain predictions.

We apply the following selection rules to avoid including bias in our DealScan sample and to provide a realistic insight on the structure of syndicates. First, we restrict our sample to a package level instead of a facility level. In our set-up, using a facility-loan level would create a selection bias in the numbers of repeated interactions because we would artificially sum the same bank members over multiple loan facilities within a loan package.[20] Second, we drop loan packages to utilities (public services) and financial firms. Third, following Roberts (2015), we drop loans that are more likely to be amendments to existing loans, because DealScan misreports them as new loans and they do not necessarily involve new money. Finally, we categorize loans as a credit line, term A and term B and exclude term loans B because banks hold none of these loans after the syndication. Term B loans are structured specifically for institutional investors and almost entirely sold off in the secondary market (Ivashina and Sun, 2011; Irani, Iyer, Meisenzahl and Peydró, 2020). Notably, excluded term loans B constitute less than 2% of the total loans in our initial sample.[21]

Because there is no common identifier between these data sets, we hand-match DealScan with Call Reports to enrich the bank's balance sheet information. We do the initial matching via a fuzzy merge algorithm based on names and locations, and we manually review all matching results. This process links the DealScan's lender ID with the commercial bank

[20] A loan package often consists of both a term loan and a credit line facility. An additional reason for using the package level is that DealScan provides relatively limited information on the bank members at the facility level due to reporting issues.

[21] In addition, we disentangle banks from nonbanks. Specifically, we consider a loan facility to have a non-bank institutional investor if at least one institutional investor that is neither a commercial nor an investment bank is involved in the lending syndicate. Nonbank institutions include hedge funds, private equity funds, mutual funds, pension funds and endowments, insurance companies, and finance companies. To identify commercial bank lenders, we start from lenders whose type in DealScan is *U.S. Bank*, *African Bank*, *Asian-Pacific Bank*, *Foreign Bank*, *Eastern Europe/Russian Bank*, *Middle Eastern Bank*, *Western European Bank*, or *Thrift/S&L*. We manually exclude nonbank observations that DealScan classifies as banks such as General Motors Acceptance Corporation (GMAC) Commercial Finance.

ID (RSSD9001) and provides a unique linkage for each lender. With this linkage, we are also able to match information from the FRB for the banks' M&A. Because Call Reports are available on a quarterly basis, we collapse the loan data set on a quarter level and we match the date of the loan deal with the relevant quarter. For example, we match all syndicated loans that originate from January 1^{st} to March 31^{st} with Call Reports for the first quarter of that year. Similarly, we obtain information from the financial statements of the firms and their industries via Compustat using the link in Chava and Roberts (2008).

Further, to construct a measure of product information complexity, we exploit the Rauch (1999) data on the categories of product differentiation. To harmonize the trade classification with industry classification, we use OECD information and the Muendler (2009) link. Rauch (1999) sorts products into two broad categories: products traded on international exchanges and differentiated products for which branding information precludes them from being traded on exchanges or being reference priced. In addition, we use the measure of co-movement between the value added of a firm and that of its industry peers computed by Guiso and Minetti (2010) and impute this measure to the firms in our sample using the industry code.

Finally, to capture enforcement actions, we follow Delis, Staikouras and Tsoumas (2016) and use their data set from 1999 until 2010. The authors screen the websites of the three primary federal supervisors of all insured commercial and savings banks in the United States: the Federal Reserve, the Federal Deposit Insurance Corporation (FDIC), and the Office of the Comptroller of the Currency (OCC). Then, they group the formal enforcement actions by rationale into a number of categories mostly reflecting the action's severity and relation with safety and soundness issues. We include only actions related to the Basel Committee Core Principles for Effective Banking Supervision. These comprise capital adequacy and liquidity, asset quality, provisions and reserves, large exposures and exposures related to parties, internal control and audit systems, money laundering, bank secrecy, and foreign assets control. In more stringent tests, we also focus on a smaller set of particularly impactful sanctions.

The matching process yields 20,932 loans from 663 banks to 5,309 non financial firms that operate in 64 industries (two-digit SIC) from 1987 until 2014. This sample is a so-called multilevel data set, which has observations for banks and firms (lower level) and loan deals (higher level). This unique feature is particularly helpful for identification purposes. Table 1 formally defines all variables used in the empirical analysis, and Table 2 shows summary statistics.

4.2 Measuring Experience

We construct three measures of experience in the syndicated loan market, namely *Sector*, *Firm*, and *Co-lending*, using variation in bank-sector, bank-firm, and bank-bank levels, respectively. We face some data limitations in the lenders' shares. As noted above, DealScan does not report the complete allocation of shares for all the loans. For the loans with a full breakdown of shares, we allocate the exact loan portions to the individual lenders. For the remaining loans, following Giannetti and Laeven (2012) and De Haas and Van Horen (2013), we divide the loan volumes among the missing syndicate members on a pro-rata basis. For robustness, in unreported results, we also use alternative approaches such as keeping only a subsample of loans with complete information or estimating a model in which the loan shares of individual lenders is the dependent variable and obtain predictions.

$Sector - Experience_{b,s,t}$ is the total credit ($M) for outstanding loans from bank b to firms in a two-digit SIC sector s at time t over the total lending ($M) for outstanding loans by bank b to all sectors:

$$Sector - Experience_{b,s,t} = \frac{\sum_{f=1}^{F} Loan_{b,f,s,t}}{\sum_{s=1}^{S}\sum_{f=1}^{F} Loan_{b,f,s,t}}\ , \tag{21}$$

where $Loan_{b,f,s,t}$ is the credit granted (in millions of dollars) by bank b to firm f in sector s at time t. F and S capture the total number of firms and sectors, respectively. This index ranges from zero to one, with higher values reflecting higher experience in the sector in which the firm operates. $Sector - Experience$ varies at the bank-sector level (Berger et al., 2017).[22] De Jonghe, Dewachter, Mulier, Ongena and Schepens (2020) use data from

[22]For robustness, in the online appendix, we use a similar approach to construct the one-three-, and four-digit SIC classification.

the Belgian credit registry and define this measure as the bank's sector specialization. In what follows, we will use the terms sector experience and sector specialization interchangeably. In our sample, the average and median loan maturity are approximately four years. Consequently, our proxy for sector experience reflects experience accumulated over several years of managing loans. In robustness checks, we adjust our proxy for sector experience to account for loans repaid within the last year, the last two years, and the last three years, in addition to considering outstanding loans. These minor adjustments in the construction of the proxy leave our results essentially unchanged.

Following Bharath, Dahiya, Saunders and Srinivasan (2011), we construct two measures for the number of previous interactions (relationships) between a bank and a firm and between banks. $Firm-experience\ (\#loans)_{b,f,t}$ measures the number of loans from lender b to firm f in the last five years prior to the current loan. Every time a new loan originates between a firm and a bank in a specific time period, we review the borrowing record of this pair in the past five years, and we compute the number of the lender-borrower pair's lending relations. In robustness tests, we verify that the results carry through when using alternative measures of firm experience. In particular, we follow Degryse and Van Cayseele (2000) and measure the duration of the credit relationship, defined as the length of time during which the bank-firm pair has maintained a lending relationship ($Firm-experience$ $(duration)$). This measure can provide additional insights into the continuity and strength of the bank-firm link.[23]

$Co-lending\ experience\ (\#loans)_{b,j,t}$ measures the number of loans that the lead arranger b syndicated with other lenders j in the last five years prior to the current loan:

$$Co-lending\ experience_{b,j,t} = \frac{1}{\mathcal{P}\left\{B_{b,j,t}\right\}} \sum_{B_{b,j,t}} \left(Number\ of\ loans\right)_{b,j,t}, b \neq j, \qquad (22)$$

where $\mathcal{P}\left\{B_{b,j,t}\right\}$ is the total number of bank 'pairs' formed in each syndicate. To create this

[23] To further measure the intensity of the lending relationship, in robustness tests we also account for the volume of loans transacted between the lender and the firm in the preceding six years (*# loans - 6 years*). This enables us to gauge the intensity of the interaction and lending commitment. Furthermore, we experiment with using a relationship lending dummy that is equal to one if there has been a lending relationship between the bank and the firm in the past five years. This provides us with another layer of understanding, showcasing the bank's sustained interest in the firm over a significant period.

measure, 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 two lenders took in previous loans. This measure assigns a greater overlap of previous experience when in the syndicate there are banks with a higher number of bilateral interactions (loan co-sharing). This index measures the importance of prior relationships among banks.

Table B.1 (in the appendix) presents the correlation matrix for our variables of interest: sectoral experience, firm experience, and co-lending experience. While firm and co-lending experiences are positively correlated, both are negatively correlated with sectoral experience, suggesting distinct influences on the lending process.

4.3 Control Variables

Consistent with previous studies, we include several loan-level, bank-level, and firm-level control variables to rule out possible alternative explanations for our results. Loan deals mainly differ in maturity, loan type, and collateral. We control for these differences by adding the natural logarithm of *Maturity*, a dummy variable equal to one if the loan is secured with *Collateral*,[24] a dummy equal to one if the loan is a term loan, a dummy equal to one if the loan has financial covenants to control for unobservable borrower risk factors (Carey and Nini, 2007), and a dummy equal to one if *Performance pricing* is included in the loan contract to control for the borrower's business prospects (Ross, 2010).

At the firm level, we control for the natural logarithm of the market-to-book ratio (*Tobin's q*) as a proxy for the cost of equity, the ratio of net income to total assets (*ROA*) to control for profits (Adams and Ferreira, 2009), and *Firm size*, measured by the natural logarithm of total assets. Regarding bank-level control variables, we use *Total loans* as a fraction of total assets, *Deposits* as a fraction of total assets, *Tier 1* as a fraction of total assets, *Non-performing loans* as well as *Deposits HHI* to capture the concentration of retail deposits (Delis, Kokas and Ongena, 2017). In most specifications, these bank-level control variables are fully absorbed by bank-time fixed effects.

[24] Securing loans with collateral lowers the risk of a loan. However, secured loans tend to be issued by younger, riskier firms with lower cash flows (Berger and Udell, 1990).

5 Main Results

In this section, we test the main implications of the model (Testable Hypotheses 1-2).

5.1 Baseline Estimates

Table 3 presents the results for how banks' past experience affects the extensive margin of syndicated loans. In columns I through III, we regress an indicator for being the lead lender on *Sector*, *Firm* and *Co-lending experience*, respectively. In columns IV and V, we add all the experience variables. Consistent with hypothesis 2 of section 2, we estimate a positive impact of *Firm* and *Co-lending experience* on the probability of being a lead arranger. We also find that $Sector - experience$ positively impacts the probability of being a lead arranger. The results are robust across specifications and remain unaltered when we saturate the regression with supply, demand and bank-industry matching fixed effects, as noted at the bottom of the table. Economically, the estimates of column IV suggest that a one-standard-deviation increase in $Sector - experience$ (14.4%) raises the probability of being a lead arranger by 3.5%. In turn, an increase in $Firm$ and $Co - lending$ experience by one standard deviation respectively raises the probability of being a lead arranger by 15% and 6%.

In Table 4, we turn to study hypothesis 1, i.e., the impact of different forms of prior experience on the share retained by a lead arranger. To disentangle this intensive margin from the extensive margin investigated in Table 3, we focus solely on lead arrangers. When we consider the impact of the various types of experience on the intensive margin of lead arrangers' participation, we obtain strikingly different results across types of experience. While firm and co-lending experience shrink the loan share the lead arranger retains, sector experience increases the loan share of the lead arranger after controlling for credit supply (bank*year FE), banks' shifting to firms with different ratings within the same industry (industry (SIC3)*year*rating FE), and unobserved components of the time-invariant matching between banks and certain industries (bank*SIC3 FE). Economically, the impact of sector experience is sizeable: for instance, in column IV of Table 4 a one-standard-deviation increase in $Sector - experience$ raises the lead share by 3.5%. The negative effects of $Firm-$and $Co-lending-experience$ turn out to be economically less sizeable but highly statistically significant.

Recall that the lead share is viewed as a proxy for the degree of moral hazard within a lending syndicate. Thus, the estimates suggest that moral hazard within syndicates may be more severe when the lead arranger has stronger sector experience. This is consistent with the results of the theoretical model of loan syndication in section 2. In the model, a larger sectorial experience boosts the ability of a lead arranger to extract value from the liquidation and redeployment of the borrowing firm's assets in the event of loan default, thus diluting the lead arranger's incentive to monitor the loan.[25] To counteract this dilution of the monitoring incentive, participant lenders request the lead arranger to retain a larger loan share (part ii of Testable Hypothesis 1). This result on the effects of sector experience contrasts with the finding for lead lenders' experience on borrowers and co-lenders, which instead tend to reduce the lead arranger share. The theoretical model of section 2 (part i of Testable Hypothesis 1) predicted such effect, rationalizing it with the reduced monitoring cost that is faced by a lead arranger with larger borrower and co-lender experience.

While our focus in Tables 3 and 4 is on the coefficient estimates for the experience variables, it is reassuring that the estimated coefficients on the control variables tend to have the expected signs. Let us look at the control variables for loan risk, for example. Loan deals with longer maturity and more general covenants tend to be riskier and, hence, banks can be less inclined to act as lead arrangers and also retain lower shares. By contrast, collateralized loans and term loans tend to be less risky, so banks could be more inclined to act as lead arrangers. Analogous considerations hold for the firm-level control variables.

5.2 Establishing Causality: An IV Approach

Despite the broad range of loan, bank, and firm characteristics and fixed effects included in the specifications, the endogeneity of the experience variables to syndicated lending practices may bias the previous estimates. The same factors that cause individual banks to acquire expertise in certain types of loans could affect syndicated lending practices and

[25] This result is also more broadly reminiscent of the argument in Manove, Padilla and Pagano (2001) that banks can become lazy monitors when they feel protected by collateral.

alter the loan structure. This issue might bias the effort to estimate the effect of bank experience directly.

To overcome this identification challenge, we follow Favara and Giannetti (2017) and Garmaise and Moskowitz (2006) and exploit mergers between banks. Specifically, we focus on mergers between non-failed banks with assets above $1bn that are active in the syndicated loan market. For this purpose, we collect data on M&A from the FRB and identify the banks in DealScan. Then we construct instruments for *Sector*, *Firm*, and *Co-lending experience* using only the historical experience variables of the target (acquired) bank, which is mainly outside of the acquiring bank's control before the merger. We restrict attention to mergers occurring within a year preceding the origination of the syndicated loan. We also include bank, year, and industry-year-firm rating category fixed effects, thus effectively exploiting variation between banks while controlling for the industry-loan level demand and the bank's balance sheet.

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

Table 5 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.[26] The first-stage coefficient estimates are displayed in panel A. In columns I-II of the first stage (panel A), we regress the sector experience on the acquirer's sector experience and a variety of loan, bank and firm control variables. Notably, the sample set of columns I and II is different, as in column II we focus solely on lead arrangers.

The first-stage results confirm a strong and positive relationship between the instru-

[26] In the table, we instrument our measures of experience one at a time.

ment and sector experience. Economically, the estimates in column I suggest that a one standard deviation increase in the target's sector experience results in a 5% increase in sector experience for the acquiring bank. The LM-test for under-identification and the F-test for excluded instruments support the instrument validity. Similarly, in columns III-IV and V-VI, we regress the firm experience on the target's firm experience and the co-lending experience on the target's co-lending experience, respectively. The interpretation of the results is similar to columns I-II.

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

6 Mechanisms

The results in Tables 3 - 5 suggest that the type of bank experience matters for the intensive and extensive syndicate margin. In what follows, we dig deeper into the data and exploit cross-sectional variations in various dimensions that allow us to test hypotheses 3 and 4 of the theoretical model. The goal is to verify that the estimated effects of our proxies for different levels of bank experience are indeed driven by prior knowledge and information accumulated by lenders in lending syndicates. In particular, we assess whether our proxies for bank experience have a stronger impact in scenarios in which we can plausibly expect bank knowledge and information accumulated in past transactions to be more relevant. These include more informationally complex sectors and firms (Testable Hypothesis 3 in the model), scenarios in which banks' lending is more asset-based (Testable Hypothesis 4), as well as the aftermath of negative shocks to co-lenders. Such findings can further validate our identification strategy and mitigate concerns about omitted variables.

6.1 Sector Complexity and Information Sensitivity

In Table 6, we exploit data on the informational complexity of the products in the sectors to better disentangle the role of experience, especially *sector experience*. We measure the degree of product information complexity using international trade classification (SITC) data from Rauch (1999). The loan-level sample has information on Standard Industrial Classification (SIC). To link the two data sets, we use information from OECD and Muendler (2009) to harmonize SITC and SIC. The objective is to create a many-to-one mapping (from SITC to SIC); hence, in some cases, we manually review the efficiency of the mapping to avoid duplicates.

The measure in Rauch (1999) captures the share of SITC products that are neither sold on an organized exchange nor reference priced (i.e., heterogeneous products).[27] In short, a firm's product is considered to be "heterogeneous" if the product is neither sold on an exchange nor reference priced. Among the loans in our sample, 30% are linked with firms with heterogeneous products, a figure in line with Campello and Gao (2017). An industry with a higher share of heterogeneous products is more likely to be subject to informational frictions. Thus, we expect banks' sector experience to have a stronger marginal impact in such an industry, relative to an industry with less complex products (Testable Hypothesis 3 in the model).

The estimates indeed confirm that the effect of banks' sector experience is stronger for industries with high informational complexity. For example, column I of Table 6 reveals that higher sector experience in industries with heterogeneous products increases the probability that a bank active in the syndicated market will act as the lead arranger by about 42%; the baseline results suggest an increase of 12% (column V, Table 3). On the other hand, we find no significant difference between informationally complex and noncomplex industries when considering the impact of firm and co-lending experience.

In Appendix Table B.2, we exploit the rich firm-level heterogeneity in our data to further ascertain whether the effects of bank experience vary with firms' sensitivity to bank information. In columns I-IV, we consider the firm Tobin's q, and (as an inverse proxy) for

[27] Rauch (1999) classifies a good as homogeneous if it is sold in organized exchanges or if there is a reference price for it. A heterogeneous product, on the other hand, requires building a trading relationship.

informational opaqueness, we consider external debt in columns V-VIII. For each group, we subdivide the sample into *Low* and *High* based on the sample mean. We find that the impact of all types of experience on the probability of being a lead arranger is stronger for less profitable firms (lower Tobin's q). Moreover, the effects of bank experience are significantly stronger for firms with less external debt. This is in line with the hypothesis that such firms are more likely to benefit from bank experience in that they rely less heavily on bank financing.

6.2 Asset-based Lending and Asset Market Conditions

The theoretical model predicts that banks' sector-specific expertise could have a larger effect on the structure of loan syndicates when banks rely more on asset-based lending technologies and when the asset market conditions imply a larger relevance of banks' knowledge of the asset market (Testable Hypothesis 4 in the model). To capture the relevance of asset-based lending, we consider the capital intensity of firms by industry.[28] Sectorial capital intensity is likely to capture technological features of the sectors in which the firms operate and, hence, may suffer less from endogeneity issues relative to firm-level measures. In Table 7 we interact our measures of banks' experience with sectorial capital intensity (column I) and also re-estimate the baseline regressions by splitting the sample at the median capital intensity (columns II-III). Given the inherent stickiness in capital intensity, we modify our fixed effect specification to include industry*year and bank fixed effects. This adaptation allows us to exploit variations in our data set without inadvertently eliminating crucial aspects of the persistent nature of asset-market conditions. The results consistently suggest that the effect of sectorial experience is larger when capital intensity is higher.[29]

[28] Professionals have long differentiated between cash-flow lending (CFL) and asset-based lending (ABL), and scholars increasingly underscore their differences as well (Calomiris, Larrain, Liberti and Sturgess, 2017; Lian and Ma, 2021; Kermani and Ma, 2023). Previous studies emphasize two critical aspects of ABL. First, the underwriting process in ABL revolves primarily around the liquidation values of collateral. Second, the monitoring activity in ABL mainly focuses on the collateral itself, with a particular emphasis on accounts receivable and inventory.

[29] Appendix Table B.3 presents an additional robustness test examining *asset-based lending*. Specifically, we generate a binary indicator for each bank participating in the syndicated loan market. This indicator is set to one if a bank's relative number and volume of collateralized loans exceeds the sample mean, thus capturing banks more inclined towards asset-based lending. The variable accounts for the proportion of collateralized loans, considering both count and amount, against the bank's total lending volume. We subsequently interact *asset-based lending* with our experience variables. Again, the results support the conclusion that asset-based lending reinforces the influence of sectorial experience.

Additionally, the model predicts that the impact of banks' experience should be more pronounced when the degree of heterogeneity in the reservation price of asset buyers is smaller (that is, η is lower in the model). As an inverse measure of heterogeneity in asset buyers' reservation price, we use the comovement of firms' value added within an industry, following Guiso and Minetti (2010) (see Table 1 for a detailed definition). Intuitively, the higher the comovement among firms' financial status in an industry, the less we expect the firms to differ in their ability and propensity to engage in the purchase of liquidated assets. Columns IV-VI report the results, first by interacting banks' sector experience with the comovement measure (column IV) and then splitting the sample at the median comovement (columns V-VI). In alignment with the model predictions, the estimated effects of sectorial experience are larger when comovement is higher, that is when the financial status of potential asset buyers in a sector is less heterogeneous.

6.3 Co-lending Experience: Sector Specificity and Trust

The baseline tests capture two forms of co-lending experience that banks can acquire. If a lending syndicate includes banks that specialize in the same sector(s), then a bank can enhance its sector information gathering through interaction with the other banks in the syndicate and coordinating with them in extending loans to firms in the sector. For a theoretical model of syndicates that can help rationalize this mechanism, see, e.g., Hatfield, Kominers, Lowery and Barry (2020). If, instead the other banks in the syndicate specialize in other sectors, experience could take the form of trust and direct acquaintance with those banks, rather than sector knowledge. We then separate our measure of co-lending experience between the number of prior loans that involve co-lending to firms that operate in the same sector and to different sectors.

In Table 8, we report the results for the impact of prior experience on the lead lender's share. The data suggest that lead arrangers tend to syndicate loans with banks that have prior experience in the same sectors. In columns I-II, we redefine *Co-lending experience* and we measure the number of loans that the lead arranger syndicated with other lenders in the sector of the current loan in the last five years normalized by the total number of bank pairs formed in each syndicate (*Co-lending experience (# loans including the same sectors)*). In columns III-IV, on the other hand, we redefine *Co-lending experience* to measure the number of loans that the lead arranger syndicated with other lenders excluding loans to the sector of the current loan in the last five years normalized by the total number of bank pairs formed in each syndicate (*Co-lending experience (# loans excluding the same sectors)*). The estimated coefficients on sector experience and firm experience are in line with the results in Table 4. Interestingly, the estimates suggest that the effect of *Co-lending experience* stems from sector familiarity instead of a trust effect (compare column I with column III and column II with column IV). In column I, we explore within-bank variation and find that the loan share the lead arranger retains decreases by one percentage point when we include only loans to the same sectors. In column II, we use a conservative specification and repeat the same analysis but this time we include bank-industry fixed effects, obtaining similar results. In column III, *Co-lending experience* takes variation only from different sectors: the estimated coefficient is statistically insignificant, though it becomes significant at the 10% level when we add bank-industry fixed effects (column IV). Moreover, the economic significance of the co-lending experience is economically less sizeable compared to columns I and II.

In columns V to VIII, we repeat the same analysis only for industries with heterogeneous products. We find that the effect of co-lending experience in the same sectors is qualitatively and quantitatively similar to the effect estimated in columns I and II. On the other hand, the estimated coefficient on co-lending experience excluding the same sectors is insignificant in column VII and remains insignificant when we control for the bank-industry matching (column VIII). Notably, the effect of sector and firm experience is insignificant because firm and sector variation for heterogeneous products is constant and the value additional loans provide is limited.

6.4 Experience and Reputation Shocks

A scenario in which bank experience can have a pronounced effect is when negative shocks hit other members of a lending syndicate. Following a negative shock to a co-lender, a bank with prior experience could step in, replacing the co-lender hit by the shock. Based on this argument, we study the consequences of exogenous shocks to lead arrangers' reputation, captured by formal enforcement actions from regulators. In particular, we examine whether a bank (control group) that joins prior syndicates with a punished lead arranger (treated group) takes the lead arranger role in new loans with the same borrowers, and whether this is more likely if the bank has stronger experience.[30]

To measure *Post sanction*, we reconstruct the syndicated loan market on a bank-bank basis and identify active lead arrangers that receive an enforcement action. Next, we track the historical records of participants in syndicated deals with the punished lead banks. *Post sanction* equals one if the new lead arranger in a current loan was in a participant role with the punished bank in past transactions. In this analysis, we use a rich set of sanctions as a stigma on bank reputation to analyze which bank replaces the punished lead arranger.

The results are displayed in Table 9. Our regression sample includes a treated group of prior lead arrangers that receive a sanction and a control group for lead arrangers without a sanction. This regression is similar to a treatment-effects model. We find that the probability of being the lead arranger and the lead retained allocation (%) increase following *Post sanction* for higher sector, firm, and co-lending experience. These findings are consistent with the hypothesis that experience enhances the flexibility with which a bank can replace a co-lender hit by a reputation shock. They also confirm that our proxies are effectively picking up the impact of bank experience in the credit market.[31]

[30] Apart from loss of reputation, a sanction may erode a lead arranger's syndicated lending activity (Delis, Staikouras and Tsoumas, 2016). In Appendix Table B.4, we observe that punished banks reduce lending in the commercial market.

[31] In Appendix Table B.5, we perform a robustness check that narrows our focus solely to *Type 1 actions*. These actions encapsulate critical areas: adequate capital (Basel Principle 16), asset quality (Basel Principle 18), and management of loan loss provisions and exposures (Basel Principles 19-20). The goal of these actions is to enforce compliance with these principles, which are crucial for preserving the stability and credibility of financial institutions. We observe a greater economic magnitude of the effects when we restrict our analysis to *Class 1 actions*. This heightened impact could stem from the severe implications of these actions for a bank's financial health and stability.

7 Robustness and Extensions

7.1 Robustness Tests

In Table 10, we further subject our findings to a variety of robustness tests. In columns I-II, we add firm fixed effects to control for time-invariant loan demand at the firm level. Borrowers who choose lenders with higher levels of experience could in fact have systematically different needs. The results are qualitative and quantitatively similar to the baseline estimates. In columns III-IV, we keep data only for loans in which the syndicate members (banks and firm) are repeated. This allows for a powerful test because, given the inclusion of bank-year fixed effects, only the time variation in experience variables drive changes in the dependent variables. The results are very close to those for the baseline specifications, showing that our findings are robust to concerns arising from differences in the structure of the syndicate.

In columns V-VI of Table 10 we exclude NBER recessions, as defined by the NBER's Business Cycle Dating Committee, as recessions may correlate with other drivers of syndication decisions. In columns VII-VIII, we drop loans in which the lead arranger is one of the largest three U.S. banks (J.P. Morgan Chase, Bank of America, and Citigroup), based on the number of deals in which they participate. This enables us to verify that the results are not driven solely by the efficiency of very large banks in originating large loan deals.

In Table 11, we experiment with an alternative indicator that is sometimes used to capture lenders' information advantage in extending loans. This indicator is based on the work of Giannetti and Saidi (2019b), who explore how a concentrated banking system absorbs the negative ripple effects from industry downturns. They conclude that, in an attempt to mitigate potential fire sales, banks increase lending to sectors affected by negative shocks because they internalize the negative spillovers of their credit contractions. Our argument differs from that of Giannetti and Saidi (2019b) in critical aspects. Giannetti and Saidi (2019b), in fact, underscore the absence of correlation between a bank's industry concentration and specialization. More in general, these measures can capture very different dimensions: concentration reveals how important a bank is for a sector while specialization reveals how important a sector is in a bank's portfolio. We follow De Jonghe, Dewachter, Mulier, Ongena and Schepens (2020) and calculate the sector shares as the ratio of total credit granted by bank b to sector s at time t relative to all credit granted by all banks to sector s:

$$Sector^{Shares}_{b,s,t} = \frac{\sum_{f=1}^{F} Loan_{b,f,s,t}}{\sum_{b=1}^{B}\sum_{f=1}^{F} Loan_{b,f,s,t}}. \tag{23}$$

This index ranges from zero to one, with higher values reflecting a greater importance of bank b to sector s. This is a structural characteristic which reveals how important a bank is for a specific sector. We reestimate our baseline specification controlling for *Sector shares*. The estimated coefficients on our variables of interest are essentially unchanged. More interestingly, the coefficient of *Sector shares* is economically less sizeable compared to the main coefficients of interest.

In Appendix Table B.6, we expand our sensitivity analysis by using alternative measures of *Firm experience*. We now consider the duration of the bank-firm relationship, the volume of loans between the lender and the firm in the preceding six years and a relationship lending dummy variable which takes the value of one if in the previous five years there was a lending relationship between the bank and the firm (Degryse and Van Cayseele, 2000; Bharath et al., 2011). The results obtained using these alternative measures of *Firm experience* are in line with those presented in Table 4. Also, in Appendix Table B.7, we present sensitivity analysis using the one-, three-, and four-digit industry classifications to measure sector experience. The results are qualitatively similar to the baseline. However, as expected, the economic significance of the estimated coefficients of interest increases as we use a more disaggregated SIC classification.

In addition, the theoretical considerations discussed earlier, especially those in Boot and Thakor (2000), suggest that there may be a non-linear effect of banks' learning by experience. To this end, in Appendix Table B.8, we examine whether the effect of different dimensions of bank experience is nonlinear by adding its squared term. The results confirm the patterns uncovered in the main tests. At the same time, they provide suggestive evidence of some non-linearity in the relation between bank experience in all measures (*Sector, Firm and Co-lending*) and the intensive and extensive margin.

7.2 Firm Outcomes

In this section we explore how banks' experience affects firm outcomes in the year after the loan origination. Table 12 displays the results. Notably, in this set-up, we are mainly interested in determining whether a conditional correlation between the banks' experience and firm outcomes at *t+1* exists, and not with identifying a causal relation between experience and firm outcomes. Thus, we are interested only in reducing the omitted-variable bias by inserting bank-year and industry-year fixed effects to saturate credit supply and industry demand factors. In the regressions we include loan control variables and the lagged dependent variable (at time *t*) as an explanatory variable of *t+1* in order to capture persistence. In all specifications, the coefficient on the lagged dependent variable is positive and statistically significant.

In column I of Table 12, the dependent variable is the natural logarithm of the firm's total assets at *t+1*. We observe that the sector and co-lending experience have a positive and significant effect on firm size. Specifically, the point estimate suggests that a one-standard-deviation increase in sector experience is associated with an increase in firm size of 14 percentage points. This is consistent with theories in which closer lender monitoring has a positive impact on future firm performance (Boot and Thakor, 2000). However, we also find that firm experience has a negative and significant effect on firm size, though the effect is economically less sizeable.[32] In the rest of the tests, we find qualitatively and quantitatively similar estimates when we replace the dependent variable with *Sales* as a proxy for firm efficiency (column II), *ROA* as a proxy for firm profitability (column III), and a *Dividend* dummy equal to one if a firm distributes a dividend in the year after the loan origination (column IV).

8 Conclusions

Experience is traditionally viewed as a fundamental mechanism of acquisition of information and knowledge in the banking sector. The way credit market experience influences

[32] Relationship lending is a crucial mechanism to mitigate moral hazard and adverse selection problems. However, banks' acquisition of private information could effectively "lock in" firms and allow banks to extract higher rents.

the monitoring activity of banks, and hence the extent of moral-hazard issues, is however relatively underexplored. To address this question, we study theoretically and empirically how three forms of bank experience (experience with borrowing firms, sector experience, and experience with co-lender banks) affect credit market outcomes.

The results suggest that firm experience and co-lending experience both incentivize banks' screening and monitoring efforts, thereby mitigating moral-hazard issues in lending syndicates. By contrast, we find evidence that sector experience exacerbates moral-hazard issues. Exploiting cross-section heterogeneity across firms and banks, we further find that the dilution of banks' monitoring incentives induced by sector experience is particularly pronounced for industries and products with high information complexity. We rationalize these findings in a model where experience can reduce the costs of monitoring borrowers, thus easing banks' monitoring efforts, but sector experience also improves banks' ability to extract value from asset liquidation in the event of loan default, thereby diluting banks' monitoring incentives.

The analysis leaves relevant questions open. In the paper, for example, we document that, by affecting moral-hazard issues in lending syndicates, experience also gives banks flexibility in responding to negative shocks hitting co-lenders. This dynamic view of bank experience could yield new insights into the role of banks in the aftermath of shocks. Further, recent studies find that lending experience can be held by loan officers rather than at the level of banking institutions (Gao, Kleiner and Pacelli, 2020; Bushman et al., 2021). One could then explore the implications of this finding for the effects of experience on loan arrangements and lending outcomes. We leave these and other relevant issues to future research.

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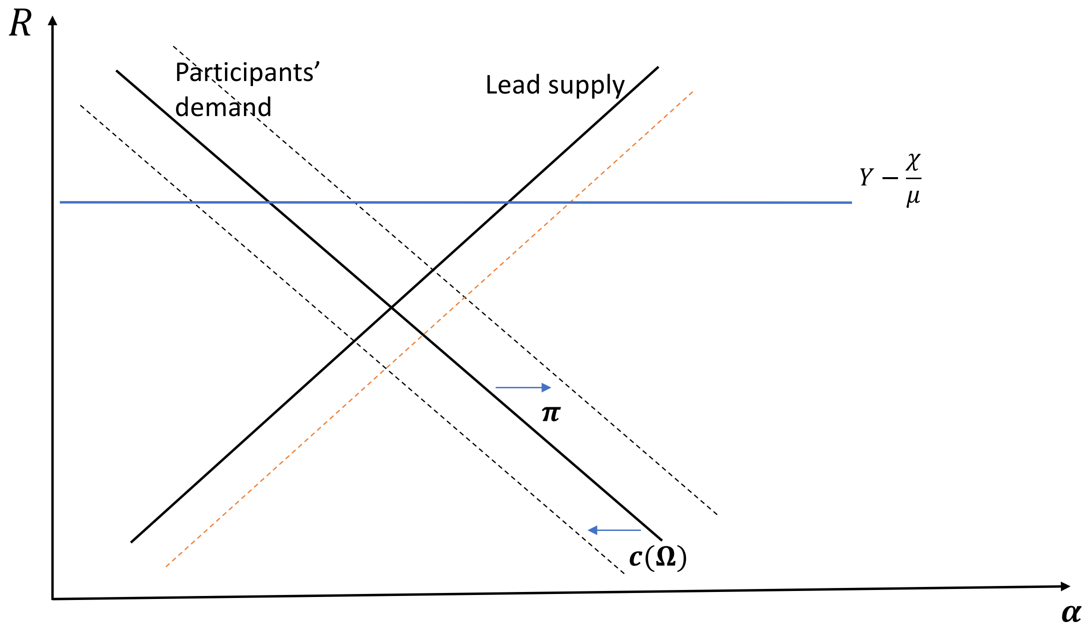
Figures

Figure 1: Supply and demand curve



The downward sloping, participant-demand curve represents the lead share demand of the participants, meant as the lead share that induces them to participate for a given repayment. The upward sloping, lead-supply curve indicates the share under which a bank is willing to act as a lead arranger.

Tables

Table 1: Variable definitions and sources

Name	Description	Source
Dependent variables:		
Lead bank	Dummy variable equal to one if the bank is the is acting as a mandate arranger, arranger, lead manager or agent and zero otherwise.	DealScan
Lead shares (%)	The share of the loan retained by the lead lender.	DealScan
Main explanatory variable:		
Sector experience (SIC2)	The amount (\$M) that bank b lends to a firm classified on a two-digit SIC sector s at time t over the total amount of lending (\$M) from bank b to the total number of sectors (S). This index ranges from zero to one, with higher values reflecting higher exposure in the sector in which the firm operates.	Own calculations
Firm experience (# loans)	The number of loans a bank lends to the same borrower in the last five years prior to a current loan.	Own calculations
Firm experience (duration)	Firm experience (duration) is the length of time the bank and firm have maintained a lending relationship. It is defined as the number of years between the first and last loan originated between a specific bank and firm pair in our sample.	Own calculations
Co-lending experience (# loans)	The number of loans the lead arranger syndicates with participant lenders in the last five years prior to a current loan. For the exact formula, see equation (22).	Own calculations
Loan-level explanatory variables:		
Maturity	The natural logarithm of loan maturity in months.	DealScan
Collateral	Dummy variable equal to one if the loan is secured with collateral and zero otherwise.	DealScan
Term	Dummy variable equal to one if the loan type is a term loan.	DealScan
General covenants	The number of general covenants (intensity), taking values from zero to nine.	DealScan
Performance pricing	Dummy variable equal to one if the loan has performance-pricing provisions and zero otherwise.	DealScan
Firm-level explanatory variables:		
Tobin's q	The natural logarithm of market-to-book value.	Compustat
ROA	Return on Assets.	Compustat
Firm size	The natural logarithm of the firm's total assets.	Compustat
Dividend	Dummy variable equal to one if a firm has a dividend payout policy.	Compustat
Firm rating category	Indicator variable for investment grade, non-investment grade and unrated firms.	Compustat
Bank-level explanatory variables:		

Total loans	Total loans over total assets.	Call reports
Deposits	Total deposits over total assets.	Call reports
Tier 1	Tier 1 capital over total assets.	Call reports
NPLs	Nonperforming loans.	Call reports
HHI-deposits	Deposits HHI.	Call reports
Cross-sectional variation:		
Product complexity	A dummy equal to one if an industry produces heterogeneous goods. We use Rauch (1999) data on the categories of product differentiation: those traded on international exchanges, those with reference prices, or those with differentiated goods for which branding information precludes them from being traded on exchanges or reference priced.	Rauch (1999)
Capital intensity	A dummy variable equal to one when an industry's capital intensity exceeds the sample mean capital intensity and zero otherwise. Capital intensity is defined as the value of physical capital in the industry, per worker.	Own calculations
Firm value comovement	A dummy variable equal to one when a firm's value comovement exceeds the sample mean comovement and zero otherwise. The measure of co-movement of firms' value is from Guiso and Minetti (2010), who compute it using data from Compustat firms over the period 1950-2000 for a total of 251,782 firm-year observations. Guiso and Minetti (2010) classify into 64 industries using a two-digit classification and then, for each industry, regress the standardized annual rate of growth of firms' sales on a full set of year dummies. If firms within an industry co-move significantly, the year dummies will explain a large part of sales variability. They thus retain the R2 of these regressions and use it as a measure of co-movement of firms in the industry. Industries with high R2 will be high comovement industries. We impute this measure to the firms in our sample using the industry code.	Guiso and Minetti (2010)
Asset-based lending	Asset-based lending is a binary indicator equal to one if a bank's relative number and volume of collateralized loans exceed the mean across the entire sample. Specifically, it measures the proportion of collateralized loans compared to the bank's total lending volume, and the proportion of the amount lent in collateralized loans relative to the total loan amount. This variable effectively identifies banks with a greater propensity towards asset-based lending.	Own calculations

Sanction	Dummy variable equal to one when an enforcement action is imposed on a bank and zero otherwise. Enforcement actions include all actions (penalties) against banks for breaches of laws and regulations in a number of cases. These cases include laws and regulations related to the Basel Committee Core Principles for Effective Banking Supervision (i.e., capital adequacy and liquidity, asset quality, provisions and reserves, large exposures and exposures related to parties, internal control and audit systems, money laundering, bank secrecy, consumer protection, and foreign assets control). They also include breaches of requirements concerning the fitness and propriety of banks' board members and senior management, as well as other persons closely associated with banks (institution-affiliated parties).	FED, FDIC, and OCC
Post sanction	Dummy variable equal to one when a bank participates in a previous syndicated loan and the lead arranger receives a regulatory enforcement action.	Own calculations
Sector shares (SIC2)	The amount ($M) bank b lends to a firm classified on a two-digit SIC sector s at time t over the total credit of the sector (s). This index ranges from zero to one, with higher values reflecting higher concentration.	Own calculations

Table 2: Summary statistics

Variables	Level	Obs.	Mean	Std. Dev.	Min.	Median	Max.
Panel A: Summary statistics							
Lead bank	Bank	61,932	0.243	0.429	0.000	0.000	1.000
Lead shares (%)	Bank	61,932	45.879	34.343	0.000	33.333	100
Sector experience (SIC1)	Bank	61,932	0.177	0.158	0.000	0.138	1.000
Sector experience (SIC2)	Bank	61,932	0.075	0.144	0.000	0.031	1.000
Sector experience (SIC3)	Bank	61,932	0.055	0.136	0.000	0.013	1.000
Sector experience (SIC4)	Bank	61,932	0.051	0.134	0.000	0.010	1.000
Firm experience (# loans)	Bank	61,932	0.238	0.981	0.000	0.000	35.000
Firm experience (duration)	Bank	53,103	4.418	4.381	0.000	3.143	16.999
Bank experience (# loans)	Bank	61,932	0.586	3.222	0.000	0.000	72.000
Maturity	Loan	61,932	3.587	0.740	-2.708	3.871	5.892
Collateral	Loan	61,932	0.376	0.484	0.000	0.000	1.000
Term	Loan	61,932	0.071	0.258	0.000	0.000	1.000
General covenants	Loan	61,932	2.419	2.603	0.000	2.000	9.000
Performance pricing	Loan	61,932	0.507	0.500	0.000	1.000	1.000
Tobin's q	Firm	61,932	1.740	2.367	0.335	1.423	203.467
ROA	Firm	61,932	0.022	0.305	0.000	0.009	31.335
Firm size	Firm	61,932	7.242	1.824	-1.966	7.232	14.571
Dividend	Firm	61,932	0.583	0.492	0.000	1.000	1.000
Total loans	Bank	61,932	0.587	0.155	0.000	0.611	1.055
Deposits	Bank	61,932	0.605	0.194	0.000	0.648	0.984
Tier1	Bank	42,040	0.076	0.042	0.000	0.068	0.980
NPLs	Bank	61,908	0.009	0.016	0.000	0.000	0.271
HHI-deposits	Bank	61,932	0.019	0.014	0.005	0.019	0.058
Product complexity	Firm	21,961	0.300	0.100	0.000	0.000	1.000
Capital intensity	Firm	32,526	0.183	0.386	0.000	0.000	1.000
Firm value comovement	Firm	61,932	0.455	0.498	0.000	0.000	1.000
Asset-based lending	Bank	61,932	0.108	0.311	0.000	0.000	1.000
Sector shares (SIC2)	Bank	61,932	0.229	0.261	0.000	0.118	1.000
Sanction	Bank	34,012	0.103	0.304	0.000	0.000	1.000
Post sanction	Loan	28,237	0.054	0.226	0.000	0.000	1.000
Panel B: Variation for the main variables of interest							
	Between	Within					
Sector experience (SIC2)	0.356	0.099					
Firm experience (# loans)	0.238	0.955					
Bank experience (# loans)	0.371	3.030					

The table provides descriptive statistics. Panel A reports summary statistics for the main variables used in analysis. Panel B shows that most of the variation in the variables of interest is within banks as opposed to sectoral specialization (between banks over time). The variables are defined in table 1.

Table 3: Experience and the likelihood of being chosen as a lead arranger

	I	II	III	IV	V
Sector experience (SIC2)	0.238***			0.209***	0.121***
	[6.303]			[6.698]	[4.669]
Firm experience (# loans)		0.169***		0.163***	0.132***
		[23.309]		[25.144]	[15.646]
Co-lending experience (# loans)			0.024***	0.019***	0.015***
			[4.895]	[4.672]	[5.131]
Maturity	-0.059***	-0.046***	-0.059***	-0.047***	-0.042***
	[-10.981]	[-8.034]	[-10.782]	[-8.022]	[-8.757]
Collateral	0.058***	0.048***	0.060***	0.050***	0.032***
	[7.042]	[7.286]	[7.353]	[7.445]	[4.874]
Term	0.054***	0.044***	0.056***	0.047***	0.038***
	[6.883]	[5.649]	[7.077]	[5.964]	[4.265]
General covenants	-0.023***	-0.021***	-0.024***	-0.022***	-0.016***
	[-10.841]	[-10.533]	[-10.728]	[-10.536]	[-8.818]
Performance pricing	-0.046***	-0.034***	-0.046***	-0.035***	-0.027***
	[-6.077]	[-4.932]	[-6.522]	[-5.301]	[-4.389]
Tobin's q	-0.001	-0.000	-0.001	-0.000	-0.001
	[-1.042]	[-0.621]	[-0.997]	[-0.673]	[-1.208]
ROA	0.003	0.003	0.003	0.003	0.003
	[0.351]	[0.494]	[0.417]	[0.546]	[0.711]
Firm size	-0.086***	-0.083***	-0.086***	-0.085***	-0.077***
	[-12.125]	[-13.274]	[-12.071]	[-13.254]	[-10.045]
Observations	59,262	59,262	59,262	59,262	56,060
R-squared	0.394	0.510	0.417	0.525	0.537
Year FE					Y
Industry (SIC3)*Year*Rating FE	Y	Y	Y	Y	
Bank*Year FE	Y	Y	Y	Y	
Bank*Industry (SIC3) FE					Y
Clustered standard errors	Bank	Bank	Bank	Bank	Bank

The table reports coefficients and t-statistics (in brackets) for lenders that are lead arrangers at least once within the five years before a loan is announced. We estimate the regression:

$$Prob(lead_{b,f,s,t}) = \alpha^{'} + \lambda_1 * Sector^{Exper}_{b,s,t} + \lambda_2 * Firm^{Exper}_{b,f,t} + \lambda_3 * Co{-}lending^{Exper}_{b,t} + \beta_1 * L_{l,t} + \beta_2 * F_{f,t-1} + \epsilon_{b,f,s,t}$$

where b, f, s, t refer to bank, firm, sector, and year, respectively. We estimate the regression on a loan-level sample originated from 1987 to 2014. All variables are defined in Table 1. All specifications are estimated with a linear probability model and include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. Standard errors are robust and clustered at the bank level. The *,**,*** marks denote the statistical significance at the 10, 5, and 1% level, respectively.

Table 4: Experience and lead lender shares (%)

	I	II	III	IV	V
Sector experience (SIC2)	23.077***			22.492***	25.756***
	[3.088]			[3.005]	[5.479]
Firm experience (# loans)		-0.977***		-0.992***	-0.522***
		[-5.247]		[-5.410]	[-3.408]
Co-lending experience (# loans)			-0.709**	-0.708**	-0.593***
			[-2.407]	[-2.410]	[-3.053]
Maturity	-7.835***	-7.945***	-7.807***	-7.887***	-7.342***
	[-11.835]	[-11.835]	[-11.686]	[-11.739]	[-13.011]
Collateral	4.744***	4.874***	4.557***	4.509***	4.264***
	[5.711]	[5.950]	[5.443]	[5.521]	[5.315]
Term	8.489***	8.580***	8.279***	8.364***	8.159***
	[7.859]	[7.919]	[7.529]	[7.734]	[9.364]
General covenants	-2.850***	-2.821***	-2.768***	-2.737***	-2.274***
	[-7.162]	[-6.970]	[-7.124]	[-6.956]	[-6.108]
Performance pricing	-6.406***	-6.412***	-6.079***	-6.239***	-5.588***
	[-5.138]	[-5.262]	[-4.957]	[-5.183]	[-4.367]
Tobin's q	-0.094	-0.103	-0.093	-0.092	-0.137*
	[-0.943]	[-1.042]	[-0.962]	[-0.953]	[-1.960]
ROA	-0.487	-0.504	-0.423	-0.458	0.026
	[-1.281]	[-1.328]	[-1.087]	[-1.223]	[0.061]
Firm size	-9.165***	-8.841***	-8.797***	-8.609***	-8.343***
	[-11.013]	[-11.013]	[-10.942]	[-11.063]	[-10.472]
Observations	14,067	14,067	14,067	14,067	16,144
R-squared	0.742	0.742	0.746	0.748	0.680
Year FE					Y
Industry (SIC3)*Year*Rating FE	Y	Y	Y	Y	
Bank*Year FE	Y	Y	Y	Y	
Bank*Industry (SIC3) FE					Y
Clustered standard errors	Bank	Bank	Bank	Bank	Bank

The table reports coefficients and t-statistics (in brackets) for lead lenders. We estimate the regression:

$$Lead\ shares(\%)_{b,f,s,t} = \alpha' + \lambda_1 Sector^{Exper}_{b,s,t} + \lambda_2 Firm^{Exper}_{b,f,t} + \lambda_3 Co{-}lending^{Exper}_{b,t} + \beta_1 L_{l,t} + \beta_2 F_{f,t-1} + \epsilon_{b,f,s,t}$$

where b, f, s, t refer to bank, firm, sector, and year, respectively. We estimate the regression on a loan-level sample originated from 1987 to 2014. All variables are defined in Table 1. All specifications include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. Standard errors are robust and clustered at the bank level. The *,**,*** marks denote the statistical significance at the 10, 5, and 1% level, respectively.

Table 5: Instrumental variables estimation using acquired (M&As) bank experience

	I	II	III	IV	V	VI
	Panel A: First-stage results					
Acquired sector experience	0.178***	0.197***				
	[16.914]	[8.215]				
Acquired firm experience			0.059***	0.110***		
			[5.248]	[4.260]		
Acquired co-lending experience					0.001***	0.001***
					[77.994]	[58.882]
	Panel B: Second-stage results with fitted values per experience variable					
Dependent variable:	Prob(lead)	Lead shares (%)	Prob(lead)	Lead shares (%)	Prob(lead)	Lead shares (%)
Sector experience (SIC2)	0.201**	24.951*	0.085***	5.155*	0.085***	4.895*
	[2.467]	[1.945]	[4.503]	[1.852]	[4.825]	[1.780]
Firm experience (# loans)	0.148***	-0.909***	0.134***	-3.740	0.151***	-1.486***
	[30.344]	[-3.852]	[3.212]	[-1.059]	[30.560]	[-5.832]
Co-lending experience (# loans)	0.018***	-0.837***	0.019***	-0.969***	0.015***	-0.744***
	[26.053]	[-15.278]	[13.317]	[-15.001]	[20.943]	[-11.663]
Loan controls	Y	Y	Y	Y	Y	Y
Bank controls	Y	Y	Y	Y	Y	Y
Firm controls	Y	Y	Y	Y	Y	Y
Observations	40,464	9,168	40,464	7,950	40,464	7,950
R-squared	0.236	0.208	0.236	0.224	0.236	0.235
F-stat	264.1	120.8	189.6	118	247.7	113.6
LM-test for under identification	274.5	74.10	34.06	28.11	498.9	319.8
F-stat for weak identification	99.37	23.08	9.210	6.567	1532	914.7
Year FE	Y	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y
Industry (SIC3)*Time*Rating FE	Y	Y	Y	Y	Y	Y
Clustered standard errors	Bank	Bank	Bank	Bank	Bank	Bank

The table reports coefficients and t-statistics (in brackets) from a 2SLS estimation. The first-stage regressions are given in Panel A. The instruments are the *sector*, *firm*, and *co-lending* experience variables of the target bank (acquired) one year before the loan origination. Panel B reports the second-stage regressions for each category. We estimate this regression on a loan-level sample originated from 1987 to 2014. The LM statistic is distributed as chi-square under the null that the equation is underidentified. The F-stat for excluded instruments is distributed as chi-square under the null of exogeneity. All variables are defined in Table 1. All specifications include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity and the following loan, bank and firm control variables: *Maturity*, *Collateral*, *Term*, *General covenants*, *Performance pricing*, *Bank size*, *NPLs*, *Deposits*, *Tobin's q*, *ROA*, and *Firm size*. Standard errors are robust and clustered at the bank level. The *,**,*** marks denote the statistical significance at the 10, 5, and 1% level, respectively.

Table 6: Experience and product information complexity

	I	II	III	IV
Dependent variable:	Prob(lead)		Lead shares (%)	
Group:	Complex	Non-complex	Complex	Non-complex
Sector experience (SIC2)	0.424***	0.197***	32.566**	25.320***
	[3.258]	[5.873]	[2.158]	[2.695]
Firm experience (# loans)	0.175***	0.160***	-1.178**	-0.831***
	[13.488]	[26.302]	[-2.531]	[-2.950]
Co-lending experience (# loans)	0.017***	0.019***	-0.616***	-0.765***
	[4.334]	[4.706]	[-3.204]	[-2.649]
Chow test (P-value)	0.000	0.000	0.000	0.000
Loan controls	Y	Y	Y	Y
Firm controls	Y	Y	Y	Y
Observations	10,440	50,858	2,320	9,077
R-squared	0.549	0.528	0.803	0.755
Bank*Year FE	Y	Y	Y	Y
Industry (SIC3)*Year*Rating FE	Y	Y	Y	Y
Clustered standard errors	Bank	Bank	Bank	Bank

The table reports coefficients and t-statistics (in brackets) for different sub samples based on Rauch (1999) classification of product information complexity. We estimate the regression:

$$Y_{b,f,s,t} = \alpha' + \lambda_1 Sector^{Exper}_{b,s,t} + \lambda_2 Firm^{Exper}_{b,f,t} + \lambda_3 Co{-}lending^{Exper}_{b,t} + \beta_1 L_{b,t} + \beta_2 F_{f,t-1} + \epsilon_{b,f,s,t}$$

where b, f, s, t refer to bank, firm, sector, and year, respectively. The dependent variable is defined in the first row. We estimate this regression on a loan-level sample originated from 1987 to 2014. We also report p-values of a Chow test of differences in the experience estimated coefficients between the two sub-groups under the null of $H_0 : \widehat{\beta}^{Complex} = \widehat{\beta}^{Non-complex}$. All variables are defined in Table 1. All specifications include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity and the following loan and firm control variables: $Maturity$, $Collateral$, $Term$, $General\ covenants$, $Performance\ pricing$, $Tobin's\ q$, ROA, and $Firm\ size$. Standard errors are robust and clustered at the bank level. The *,**,*** marks denote the statistical significance at the 10, 5, and 1% level, respectively.

Table 7: Experience and asset market conditions

	I	II	III	IV	V	VI
Dependent variable:	Lead shares (%)					
Group:	Capital intensity			Firm value comovement		
Category:	Interaction	Above≥50%	Below<50%	Interaction	Above≥50%	Below<50%
Sectoral experience (SIC2)	9.203***	29.058***	11.897***	8.886**	34.831**	10.284**
	[2.906]	[4.326]	[3.603]	[2.156]	[2.152]	[2.561]
Firm experience (# loans)	-1.150***	-0.897***	-1.061***	-0.944***	-1.457***	-0.834***
	[-4.978]	[-3.664]	[-4.546]	[-5.134]	[-2.820]	[-4.608]
Co-lending experience (# loans)	-0.808***	-0.576**	-0.802***	-0.655**	-0.405**	-0.628**
	[-3.026]	[-2.151]	[-2.799]	[-2.440]	[-2.088]	[-2.236]
Sectoral experience (SIC2) * group	17.187***			23.682*		
	[3.029]			[1.897]		
Firm experience (# loans) * group	0.361			-0.103		
	[1.040]			[-0.200]		
Co-lending experience (# loans) * group	0.214***			0.282***		
	[3.403]			[3.361]		
Loan controls	Y	Y	Y	Y	Y	Y
Bank controls	Y	Y	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y	Y	Y
Observations	8,769	1,303	7,418	16,900	6,538	10,292
R-squared	0.666	0.577	0.676	0.677	0.628	0.699
Industry (SIC3)*Year FE	Y	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y
Clustered standard errors	Bank	Bank	Bank	Bank	Bank	Bank

The table reports coefficients and t-statistics (in brackets). We estimate the regression:

$$Y_{b,f,s,t} = \alpha^{'} + \lambda_1 Sector^{Exper}_{b,s,t} + \lambda_2 Firm^{Exper}_{b,f,t} + \lambda_3 Co-lending^{Exper}_{b,t} + \beta_1 L_{b,t} + \beta_2 F_{f,t-1} + \epsilon_{b,f,s,t}$$

where b, f, s, t refer to bank, firm, sector, and year, respectively. The dependent variable is the lead lender shares (%), reported in the first line. We estimate the regression on a loan-level sample originated from 1987 to 2014. Column I displays the interaction of sectoral, firm, and co-lending experience with *capital intensity*. Columns II and III focus on subsamples split by firms' capital intensity being above (Column II) or below (Column III) the median. Similarly, column IV displays the interaction for firm value comovement, with columns V and VI presenting sub-samples for firms above and below the median of firm value comovement, respectively. All variables are defined in Table 1. All specifications include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity and the following loan, bank and firm control variables: $Maturity$, $Collateral$, $Term$, $General\ covenants$, $Performance\ pricing$, $Bank\ size$, $NPLs$, $Deposits$, $Tobin's\ q$, ROA, and $Firm\ size$. Standard errors are robust and clustered at the bank level. The *,**,*** marks denote the statistical significance at the 10, 5, and 1% level, respectively.

Table 8: Experience and sector similarity

	I	II	III	IV	V	VI	VII	VIII
Dependent variable:	Lead shares (%)							
Group:					Sectors with information complexity			
Sector experience (SIC2)	4.771	18.644***	21.355***	21.222***	-17.239	5.662	6.782	19.740*
	[0.673]	[3.965]	[5.085]	[3.958]	[-0.785]	[0.605]	[0.314]	[1.792]
Firm experience (# loans)	-0.840*	-0.282	-0.190	-0.098	-0.105	-0.038	-0.561**	-0.214
	[-1.945]	[-1.010]	[-1.589]	[-0.866]	[-0.103]	[-0.091]	[-2.196]	[-1.281]
Co-lending experience (# loans including the same sectors)	-0.929**	-0.818***			-0.641***	-0.735***		
	[-2.223]	[-2.793]			[-2.945]	[-3.615]		
Co-lending experience (# loans excluding the same sectors)			-0.067	-0.052*			-0.129	-0.089
			[-1.596]	[-1.898]			[-1.306]	[-1.189]
Loan controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	4,351	5,776	9,034	9,928	483	857	1,223	1,532
R-squared	0.805	0.751	0.624	0.462	0.906	0.784	0.653	0.483
Year FE		Y		Y		Y		Y
Bank*Year FE	Y		Y		Y		Y	
Industry (SIC3)*Year*Rating FE	Y		Y		Y		Y	
Bank*Industry (SIC3) FE		Y		Y		Y		Y
Clustered standard errors	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

The table reports coefficients and t-statistics (in brackets). We estimate the regression:

$$Lead\ shares(\%)_{b,f,s,t} = \alpha' + \lambda_1 Sector^{Exper}_{b,s,t} + \lambda_2 Firm^{Exper}_{b,f,t} + \lambda_3 Co-lending^{Exper}_{b,t} + \beta_1 L_{b,t} + \beta_2 F_{f,t-1} + \epsilon_{b,f,s,t}$$

where b, f, s, t refer to bank, firm, sector, and year, respectively. *Co-lending experience (# loans including the same sectors)* measures the number of loans that the lead arranger syndicated with other lenders in the sector of the current loan in the last five years normalized by the total number of bank pairs formed in each syndicate. *Co-lending experience (# loans excluding the same sectors)* measures the number of loans that the lead arranger syndicated with other lenders excluding loans to the sector of the current loan in the last five years normalized by the total number of bank pairs formed in each syndicate. We estimate the regression on a loan-level sample originated from 1987 to 2014. The dependent variable is reported in the second line. In columns V-VIII we use a sub-sample only for firms that operate in industries with differentiated products (complex products) following Rauch (1999). All variables are defined in Table 1. All specifications include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity and the following loan and firm control variables: $Maturity$, $Collateral$, $Term$, $General\ covenants$, $Performance\ pricing$, $Tobin's\ q$, ROA, and $Firm\ size$. Standard errors are robust and clustered at the firm level. The *,**,*** marks denote the statistical significance at the 10, 5, and 1% level, respectively.

Table 9: Treatment group for post sanction members

	I	II	III	IV
Dependent variable:	Prob(Lead)		Lead shares (%)	
Sector experience (SIC2)	0.188***	0.115***	11.780	16.425***
	[5.668]	[4.204]	[0.652]	[3.655]
Firm experience (# loans)	0.147***	0.124***	-0.276	-0.285
	[10.187]	[10.304]	[-0.803]	[-1.123]
Co-lending experience (# loans)	0.021***	0.019***	-0.004	-0.920***
	[5.480]	[6.179]	[-0.029]	[-2.987]
Sanction * Sector experience (SIC2)	0.237***	0.120***	15.217**	16.425***
	[6.109]	[3.948]	[2.377]	[3.655]
Sanction * Firm experience (# loans)	0.117***	0.092***	-0.984***	-0.285
	[7.770]	[7.933]	[-2.220]	[-1.123]
Sanction * Co-lending experience (# loans)	0.028***	0.023***	-1.050**	-0.920***
	[5.740]	[7.000]	[-2.170]	[-2.987]
Loan controls	Y	Y	Y	Y
Firm controls	Y	Y	Y	Y
Post-sanction variable		Y		Y
Observations	27,337	25,330	5,237	5,776
R-squarred	0.558	0.603	0.798	0.773
Year FE		Y		Y
Industry (SIC3)*Year*Rating FE	Y		Y	
Bank*Year FE	Y		Y	
Bank*Industry (SIC3) FE		Y		Y
Clustered standard errors	Bank	Bank	Bank	Bank

The table reports coefficients and t-statistics (in brackets). We estimate the regression:

$$Y_{b,f,s,t} = \alpha^{'} + \lambda_1 Sector_{b,s,t}^{Exper} + \lambda_2 Firm_{b,f,t}^{Exper} + \lambda_3 Co-lending_{b,t}^{Exper} + \beta_1 L_{b,t} + \beta_2 F_{f,t-1} + \epsilon_{b,f,s,t}$$

where b, f, s, t refer to bank, firm, sector, and year, respectively. We estimate the regression on a loan-level sample originated from 1999 to 2011 due to the sanctions data coverage. The dependent variable is reported in the first line. All variables are defined in Table 1. All specifications include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity and the following loan and firm control variables: *Maturity*, *Collateral*, *Term*, *General covenants*, *Performance pricing*, *Tobin's q*, *ROA*, and *Firm size*. Standard errors are robust and clustered at the bank level. The *,**,*** marks denote the statistical significance at the 10, 5, and 1% level, respectively.

Table 10: Alternative specifications

	I	II	III	IV	V	VI	VII	VIII
	Firm FE		Repeated syndicate member		Exclude NBER recessions		Exclude TOP3 banks	
Dependent variable:	Prob(lead)	Lead shares (%)	Prob(lead)	Lead shares (%)	Prob(lead)	Lead shares (%)	Prob(lead)	Lead shares (%)
Sector experience (SIC2)	0.226***	33.733***	0.128**	26.602	0.211***	18.785***	0.180***	10.280
	[7.406]	[6.533]	[2.020]	[0.528]	[8.657]	[3.798]	[5.813]	[1.237]
Firm experience (# loans)	0.163***	-0.688***	0.178***	0.607	0.163***	-1.001***	0.180***	-1.403***
	[26.408]	[-4.265]	[26.660]	[0.870]	[25.287]	[-5.167]	[17.837]	[-4.686]
Co-lending experience (# loans)	0.018***	-0.585***	0.019***	0.016	0.019***	-0.823***	0.025***	-1.720***
	[4.471]	[-2.751]	[12.581]	[0.173]	[19.626]	[-9.366]	[6.259]	[-6.641]
Loan controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	59,507	15,852	10,556	700	52,047	12,080	44,732	6,736
R-squarred	0.521	0.743	0.576	0.832	0.525	0.754	0.575	0.787
F-test	174.7	119.9	91.27	2.026	256.2	149.8	91.62	115.3
Firm FE	Y	Y						
Bank*Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry (SIC3)*Year*Rating FE			Y	Y	Y	Y	Y	Y
Clustered standard errors	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

The table reports coefficients and t-statistics (in brackets). We estimate the regression:

$$Y_{b,f,s,t} = \alpha' + \lambda_1 Sector^{Exper}_{b,s,t} + \lambda_2 Firm^{Exper}_{b,f,t} + \lambda_3 Co-lending^{Exper}_{b,t} + \beta_1 L_{b,t} + \beta_2 F_{f,t-1} + \epsilon_{b,f,s,t}$$

where b, f, s, t refer to bank, firm, sector, and year, respectively. We estimate the regression on a loan-level sample originated from 1987 to 2014. The dependent variable is reported in the third line. All variables are defined in Table 1. All specifications include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity and the following loan and firm control variables: $Maturity$, $Collateral$, $Term$, $General\ covenants$, $Performance\ pricing$, $Tobin's\ q$, ROA, and $Firm\ size$. Standard errors are robust and clustered at the bank level. The *,**,*** marks denote the statistical significance at the 10, 5, and 1% level, respectively.

Table 11: Experience and market shares

	I	II
Dependent variable:	Prob(lead)	Lead shares (%)
Sector experience (SIC2)	0.208***	21.613***
	[9.030]	[4.120]
Firm experience (# loans)	0.163***	-0.990***
	[26.783]	[-5.250]
Co-lending experience (# loans)	0.019***	-0.708***
	[18.692]	[-8.046]
Sector shares (SIC2)	0.038**	2.260
	[2.396]	[0.497]
Loan controls	Y	Y
Firm controls	Y	Y
Observations	59,262	14,067
R-squarred	0.525	0.748
Bank*Year FE	Y	Y
Industry (SIC3)*Year*Rating FE	Y	Y
Clustered standard errors	Bank	Bank

The table reports coefficients and t-statistics (in brackets). We estimate the regression:

$$Y_{b,f,s,t} = \alpha^{'} + \lambda_1 * Sector^{Exper}_{b,s,t} + \lambda_2 * Firm^{Exper}_{b,f,t} + \lambda_3 * Co-lending^{Exper}_{b,t} + \beta_1 * L_{l,t} + \beta_2 * F_{f,t-1} + \epsilon_{b,f,s,t}$$

where b, f, s, t refer to bank, firm, sector, and year, respectively. We estimate this regression on a loan-level sample originated from 1987 to 2014. All variables are defined in Table 1. All specifications include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity and the following loan and firm control variables: $Maturity$, $Collateral$, $Term$, $General\ covenants$, $Performance\ pricing$, $Tobin's\ q$, ROA, and $Firm\ size$. Standard errors are robust and clustered at the bank level. The *,**,*** marks denote the statistical significance at the 10, 5, and 1% level, respectively.

Table 12: The impact of experience on firm's outcomes after the loan origination

	I	II	III	IV
Dependent variable	$Size_{t+1}$	$Sales_{t+1}$	ROA_{t+1}	$Dividend_{t+1}$
Sector experience (SIC2)	0.992***	0.789***	0.034**	0.062**
	[10.337]	[7.822]	[2.344]	[2.459]
Firm experience (# loans)	-0.035***	-0.030***	0.001	-0.008***
	[-4.725]	[-4.089]	[1.221]	[-3.679]
Co-lending experience (# loans)	0.006***	0.006***	0.001**	0.001**
	[3.640]	[3.231]	[2.466]	[2.133]
Lagged dependent variable	Y	Y	Y	Y
Loan controls	Y	Y	Y	Y
Observations	60,148	60,148	60,148	60,148
R-squared	0.550	0.547	0.246	0.396
Bank*Year FE	Y	Y	Y	Y
Industry (SIC3)*Year FE	Y	Y	Y	Y
Clustered standard errors	Firm	Firm	Firm	Firm

The table reports coefficients and t-statistics (in brackets). We estimate the regression:

$$Y_{b,f,s,t} = \alpha^{'} + \lambda_1 * Sector^{Exper}_{b,s,t} + \lambda_2 * Firm^{Exper}_{b,f,t} + \lambda_3 * Co-lending^{Exper}_{b,t} + \beta_1 * L_{l,t} + \beta_2 * F_{f,t-1} + \epsilon_{b,f,s,t}$$

where $b, f, s, t+1$ refer to bank, firm, sector, and year, respectively. We estimate this regression on a loan-level sample originated from 1987 to 2014. The dependent variable is reported in the second line. All variables are defined in Table 1. All specifications include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity and the following loan and firm control variables: $Maturity$, $Collateral$, $Term$, $General\ covenants$, $Performance\ pricing$, $Tobin's\ q$, ROA, and $Firm\ size$. Standard errors are robust and clustered at the firm level. The *,**,*** marks denote the statistical significance at the 10, 5, and 1% level, respectively.

Online Appendix

This Online Appendix contains the proofs of the model (Appendix A) and additional empirical results (Appendix B).

Appendix A Proofs of the Model

A.1 Monitoring

Below we prove that the optimal monitoring choice of a lead lender μ is increasing in the loan share a lead lender retains, α, decreasing in the level of his sectorial experience, π, and increasing in the level of his experience Ω about the borrower and the co-lenders.

Define

$$G(\mu) = \alpha(R - p_{lead}A) - c\mu.$$

G is decreasing in μ since

$$\frac{\partial G}{\partial \mu} = -\alpha A \frac{\partial p_{lead}}{\partial \mu} - c < 0.$$

Therefore, $G(\mu) = 0$ has a unique solution between 0 and 1 if $G(0) > 0$ and $G(1) < 0$. $G(0) > 0$ is equivalent to

$$R - A\Bigg\{\tilde{L} - \eta A\Bigg\{(1-\alpha) + 2\alpha\left[\pi^2 + (1-\pi)^2\right]\Bigg\}\Bigg\} > 0,$$

a sufficient condition of which is $R > A\tilde{L}$. $G(1) < 0$ is equivalent to

$$\alpha(R - A\tilde{L}) - c < 0,$$

a sufficient condition of which is $R - A\tilde{L} < c$.

We can also show that

$$\frac{\partial G}{\partial \alpha} = R - p_{lead}A - \alpha A \frac{\partial p_{lead}}{\partial \alpha} \geq R - p_{lead}A > 0.$$

Therefore, by the implicit function theorem,

$$\frac{\partial \mu}{\partial \alpha} = -\frac{\frac{\partial G}{\partial \alpha}}{\frac{\partial G}{\partial \mu}} > 0.$$

Similarly,

$$\frac{\partial \mu}{\partial \pi} = -\frac{\frac{\partial G}{\partial \pi}}{\frac{\partial G}{\partial \mu}} = \frac{\alpha A \frac{\partial p_{lead}}{\partial \pi}}{\frac{\partial G}{\partial \mu}}.$$

Therefore, $\frac{\partial \mu}{\partial \pi} < 0$ as long as $\frac{\partial p_{lead}}{\partial \pi} > 0$, i.e, when condition (9) holds. Moreover,

$$\frac{\partial G}{\partial R} = \alpha > 0 \Rightarrow \frac{\partial \mu}{\partial R} = -\frac{\frac{\partial G}{\partial R}}{\frac{\partial G}{\partial \mu}} > 0.$$

Finally,

$$\frac{\partial G}{\partial A} = -\alpha p_{lead} - \alpha A \frac{\partial p_{lead}}{\partial A}.$$

To ensure that $\frac{\partial \mu}{\partial A} < 0$, we need $\frac{\partial G}{\partial A} < 0$, which holds when the price elasticity is small enough

$$\eta < \frac{\tilde{L}}{2(1-\mu)A\left\{(1-\alpha) + 2\alpha\left[\pi^2 + (1-\pi)^2\right]\right\}}.$$

A.2 Demand

We now show that the demand curve of participants is downward sloping, that is, participants request a lead lender to retain a lower lead share α when the repayment R is larger. Moreover, the demand schedule shifts outward when lead lenders' sectorial experience π rises, while it shifts inward when lead lenders' experience Ω about the borrower and the co-lenders increases.

Define

$$F(\alpha) = \mu R + (1-\mu) p_{par} A - 1.$$

We have

$$\begin{aligned} \frac{\partial F}{\partial \alpha} &= \frac{\partial \mu}{\partial \alpha} R - \frac{\partial \mu}{\partial \alpha} p_{par} A + (1-\mu) A \frac{\partial p_{par}}{\partial \mu} \frac{\partial \mu}{\partial \alpha} = \\ &= \frac{\partial \mu}{\partial \alpha}\left[R - p_{par} A + \eta (1-\mu) A^2\right] > 0. \end{aligned}$$

$F(\alpha) = 0$ has a unique solution between 0 and 1 when $F(0) < 0$ and $F(1) > 0$. The former inequality is equivalent to

$$A\left[\frac{1}{2}(\bar{L} + \underline{L}) - \eta A\right] - 1 < 0.$$

The fact that the demand curve is downward sloping can be inferred from

$$\frac{\partial F}{\partial R} = \mu + \frac{\partial \mu}{\partial R}\left[R - p_{par} A + (1-\mu) A \frac{\partial p_{par}}{\partial \mu}\right] > 0,$$

which implies that

$$\frac{\partial \alpha}{\partial R} = -\frac{\frac{\partial F}{\partial R}}{\frac{\partial F}{\partial \alpha}} < 0.$$

Further, we have

$$\frac{\partial F}{\partial c} = \frac{\partial \mu}{\partial c}\left[R - p_{par} A + (1-\mu) A \frac{\partial p_{par}}{\partial \mu}\right] < 0.$$

Therefore,

$$\frac{\partial \alpha}{\partial c} = -\frac{\frac{\partial F}{\partial c}}{\frac{\partial F}{\partial \alpha}} > 0.$$

That is, the demand schedule shifts inward when lead lenders' experience Ω about the borrower and the co-lenders increases, reducing the cost of monitoring (lower $c(\Omega)$). In addition,

$$\frac{\partial F}{\partial \pi} \quad = \quad \frac{\partial \mu}{\partial \pi}\left[R - p_{par}A + (1-\mu)A\frac{\partial p_{par}}{\partial \mu}\right] > 0.$$

Therefore,

$$\frac{\partial \alpha}{\partial \pi} = -\frac{\frac{\partial F}{\partial \pi}}{\frac{\partial F}{\partial \alpha}} = -\frac{\frac{\partial \mu}{\partial \pi}}{\frac{\partial \mu}{\partial \alpha}} > 0 \Longleftrightarrow \frac{\partial \mu}{\partial \pi} < 0.$$

As long as condition (9) satisfies, the demand schedule shifts outward when lead lenders' sectorial experience π rises. Moreover,

$$\frac{\partial \alpha}{\partial \pi} = \frac{\alpha A \frac{\partial p_{lead}}{\partial \pi}}{\frac{\partial G}{\partial \alpha}} = \alpha A \frac{(\overline{L} - \underline{L}) - 8\eta(\pi - \frac{1}{2})\alpha(1-\mu)A}{(R - Ap_{lead}) + 4\eta(\pi - \frac{1}{2})^2\alpha(1-\mu)A^2}.$$

When $\eta = 0$, it reduces to

$$\frac{\partial \alpha}{\partial \pi} = \alpha A \frac{\overline{L} - \underline{L}}{R - Ap_{lead}}.$$

Since both α and p_{lead} is increasing in π, it directly follows that $\frac{\partial^2 \alpha}{\partial \pi^2} > 0$. By continuity, this also holds for positive but small-enough η. One can also show that when $\eta = 0$, $\frac{\partial^2 \alpha}{\partial \pi \partial A} > 0$ if and only if

$$c > \frac{\alpha(\bar{L} + \underline{L})A}{2\left[R^2 + R\tilde{L}A - (\bar{L} + \underline{L})\tilde{L}A\right]}.$$

A.3 Supply

Here we show that the supply curve is upward sloping. Moreover, the supply schedule shifts outward when lead lenders' sectorial experience π increases and when their borrower and co-lender experience Ω rises.

We obtain

$$\frac{\partial U}{\partial \alpha} = [\mu R + (1-\mu)p_{lead}A] - \phi'(\alpha) + \alpha(1-\mu)A\left(\frac{\partial p_{lead}}{\partial \alpha} + \frac{\partial p_{lead}}{\partial \mu}\frac{\partial \mu}{\partial \alpha}\right).$$

In turn,

$$\frac{\partial U}{\partial R} = \alpha\mu + \alpha(1-\mu)A\frac{\partial p_{lead}}{\partial \mu}\frac{\partial \mu}{\partial R} > 0.$$

We have that

$$\frac{\partial U}{\partial \alpha} < 0 \Longleftrightarrow \phi'(\alpha) > [\mu R + (1-\mu)p_{lead}A] + \alpha(1-\mu)A\left(\frac{\partial p_{lead}}{\partial \alpha} + \frac{\partial p_{lead}}{\partial \mu}\frac{\partial \mu}{\partial \alpha}\right).$$

When $\eta = 0$, $\frac{\partial p_{lead}}{\partial \alpha} = \frac{\partial p_{lead}}{\partial \mu} = 0$. In this case, a sufficient condition is $\phi'(\alpha) > Y$. When the above condition is satisfied, we have $\frac{\partial \alpha}{\partial R} > 0$, i.e., the supply curve is upward-sloping.

The condition under which the supply shifts outward when sectorial experience rises is

$$\frac{\partial U}{\partial \pi} = \alpha(1-\mu)A\left[\frac{\partial p_{lead}}{\partial \pi} + \frac{\partial p_{lead}}{\partial \mu}\frac{\partial \mu}{\partial \pi}\right] > 0.$$

Since $\frac{\partial p_{lead}}{\partial \pi} > 0$ and $\frac{\partial \mu}{\partial \pi} < 0$, the above condition always holds when $\eta = 0$ and therefore $\frac{\partial p_{lead}}{\partial \mu} = 0$. By continuity, it also holds when η is positive but small enough. Next, we can also show that $\frac{\partial \alpha}{\partial \pi}$ is increasing in A and π for η small enough.

$$\frac{\partial \alpha}{\partial \pi} = -\frac{\frac{\partial U}{\partial \pi}}{\frac{\partial U}{\partial \alpha}} = -\frac{\alpha(1-\mu)A\left[\frac{\partial p_{lead}}{\partial \pi} + \frac{\partial p_{lead}}{\partial \mu}\frac{\partial \mu}{\partial \pi}\right]}{[\mu R + (1-\mu)p_{lead}A] - \phi'(\alpha) + \alpha(1-\mu)A\left(\frac{\partial p_{lead}}{\partial \alpha} + \frac{\partial p_{lead}}{\partial \mu}\frac{\partial \mu}{\partial \alpha}\right)}.$$

When $\eta = 0$, it simplifies to

$$\frac{\partial \alpha}{\partial \pi} = \frac{\alpha(1-\mu)A(\bar{L} - \underline{L})}{\phi'(\alpha) - [\mu R + (1-\mu)p_{lead}A]}.$$

In this case,

$$\begin{aligned}\frac{\partial^2 \alpha}{\partial \pi \partial A} \propto \quad & \alpha(1-\mu)\left[\phi'(\alpha) - R\mu\right] + \frac{\alpha^2 p_{lead}A\left[\phi'(\alpha) - R\right]^2}{c\left[\phi'(\alpha) - (R\mu + (1-\mu)p_{lead}A)\right]} \\ & + \frac{\partial \alpha}{\partial A}(1-\mu)A\left[\phi'(\alpha) - (\mu R + (1-\mu)p_{lead}A) - \alpha\phi''(\alpha)\right].\end{aligned}$$

Since $\frac{\partial \alpha}{\partial A} > 0$ and $R < Y$, a sufficient condition for $\frac{\partial^2 \alpha}{\partial \pi \partial A} > 0$ is that $\phi'(\alpha) - Y > 0$ and $\phi'(\alpha) - Y - \alpha\phi''(\alpha) > 0$. By continuity, when these conditions hold, $\frac{\partial^2 \alpha}{\partial \pi \partial A} > 0$ holds in the neighborhood of $\eta = 0$. In addition,

$$\begin{aligned}\frac{\partial^2 \alpha}{\partial \pi^2} \propto \quad & \alpha(1-\mu)^2 A\frac{\partial p_{lead}}{\partial \pi} + \frac{\alpha^2 A(\bar{L} - \underline{L})\left[\phi'(\alpha) - R\right]^2}{c\left[\phi'(\alpha) - (\mu R + (1-\mu)p_{lead}A)\right]} \\ & + \frac{\partial \alpha}{\partial \pi}(1-\mu)\left[\phi'(\alpha) - (\mu R + (1-\mu)p_{lead}A) - \alpha\phi''(\alpha)\right].\end{aligned}$$

Since $\frac{\partial p_{lead}}{\partial \pi} = \bar{L} - \underline{L} > 0$ and $\frac{\partial \alpha}{\partial \pi} > 0$, a sufficient condition for $\frac{\partial^2 \alpha}{\partial \pi^2} > 0$ is that $\phi'(\alpha) - Y > 0$ and $\phi'(\alpha) - Y - \alpha\phi''(\alpha) > 0$. By continuity, when these conditions hold, $\frac{\partial^2 \alpha}{\partial \pi^2} > 0$ holds in the neighborhood of $\eta = 0$.

Finally, to ensure that $U(\alpha)$ has a solution between 0 and 1, we must have $U(1) < 0$ and

$$U(0) = \kappa > 0.$$

We also have

$$\frac{\partial U}{\partial c} = \alpha(1-\mu)A\frac{\partial p_{lead}}{\partial \mu}\frac{\partial \mu}{\partial c} - \frac{\mu^2}{2} < 0.$$

Therefore,

$$\frac{\partial \alpha}{\partial c} = -\frac{\frac{\partial U}{\partial c}}{\frac{\partial U}{\partial \alpha}} < 0.$$

A.4 Robustness to delegated liquidation

Assume a simple Nash bargaining at the asset resale stage and denote by β the bargaining power of the lead lender. The lead lender expects to obtain

$$\beta(1-\alpha)(p_{lead}-p_{par})A$$

from the delegated liquidation of the participants' assets. In turn, the participant lenders expect to obtain

$$(1-\alpha)\left[(1-\beta)(p_{lead}-p_{par})+p_{par}\right]A=(1-\alpha)\left[(1-\beta)p_{lead}+\beta p_{par}\right]A.$$

Optimal monitoring. The optimal monitoring level of a lead lender now solves

$$\max_{\mu}\left\{\alpha\mu A+(1-\mu)\left[\alpha p_{lead}+\beta(1-\alpha)(p_{lead}-p_{par})\right]A-\frac{c\mu^2}{2}-\phi(\alpha)+\chi\right\}.$$

We obtain

$$\mu=\frac{\alpha R-\left[\alpha p_{lead}+\beta(1-\alpha)(p_{lead}-p_{par})\right]A}{c}.$$

Below we consider the case when $\eta=0$. We then have $p_{lead}=\pi\overline{L}+(1-\pi)\underline{L}\equiv\tilde{L}$ and $p_{par}=\frac{1}{2}(\overline{L}+\underline{L})$. Therefore, $p_{lead}-p_{par}=(\pi-1/2)(\bar{L}-\underline{L})$. Replacing into the above,

$$\mu=\frac{\alpha R-\left[\alpha\tilde{L}+\beta(1-\alpha)(\pi-\frac{1}{2})(\bar{L}-\underline{L})\right]A}{c(\Omega)}$$

Demand of lead shares. The participants' zero-profit constraint reads

$$F(\alpha)=\mu R+(1-\mu)\left[(1-\beta)p_{lead}+\beta p_{par}\right]A-1=0,$$

which when $\eta=0$ can be rewritten as

$$F(\alpha)=\mu R+(1-\mu)\left[\tilde{L}-\beta(\pi-\frac{1}{2})(\bar{L}-\underline{L})\right]A=1.$$

We obtain:

$$\frac{\partial F}{\partial\alpha}=\frac{\partial\mu}{\partial\alpha}\left[R-\tilde{L}A+\beta(\pi-\frac{1}{2})(\bar{L}-\underline{L})A\right]>0,$$

and

$$\frac{\partial F}{\partial\pi}=\frac{\partial\mu}{\partial\pi}\left[R-\tilde{L}A+\beta(\pi-\frac{1}{2})(\bar{L}-\underline{L})A\right]+(1-\mu)(1-\beta)(\overline{L}-\underline{L})A.$$

Since $\frac{\partial\mu}{\partial\pi}<0$, $\frac{\partial F}{\partial\pi}<0$ as long as β is not too small and therefore $(1-\mu)(1-\beta)(\overline{L}-\underline{L})A$ is not too large. In that case,

$$\frac{\partial\alpha}{\partial\pi}=-\frac{\frac{\partial F}{\partial\pi}}{\frac{\partial F}{\partial\alpha}}>0.$$

That is, higher sectorial π experience shifts the demand curve to the right.

Supply of lead shares. The lead lenders' zero-profit condition reads

$$U(\alpha)=\alpha\mu R+(1-\mu)\left[\alpha p_{lead}+\beta(1-\alpha)(p_{lead}-p_{par})\right]A-\frac{c\mu^2}{2}-\phi(\alpha)+\chi=0.$$

When $\eta = 0$, it can be rewritten as

$$U(\alpha) = \alpha\mu R + (1-\mu)\left[\alpha\tilde{L} + \beta(1-\alpha)(\pi - \frac{1}{2})(\bar{L} - \underline{L})\right] A - \frac{c\mu^2}{2} - \phi(\alpha) + \chi = 0.$$

We have

$$\frac{\partial U}{\partial \pi} = (1-\mu)(\alpha + \beta - \alpha\beta)(\bar{L} - \underline{L})A > 0,$$

and

$$\frac{\partial U}{\partial \alpha} = \mu R + (1-\mu)\left[\tilde{L} - \beta(\pi - \frac{1}{2})(\bar{L} - \underline{L})\right] A - \phi'(\alpha).$$

Similar to the main model, a sufficient condition for $\frac{\partial U}{\partial \alpha} < 0$ is that $\phi'(\alpha) > Y$. In this case,

$$\frac{\partial \alpha}{\partial \pi} = -\frac{\frac{\partial U}{\partial \pi}}{\frac{\partial U}{\partial \alpha}} > 0.$$

That is, higher sectorial π experience shifts the supply curve to the right.

A.5 Information complexity and lenders' experience

Here we assume that the probability that a lead lender observes a more informative signal is $\lambda\pi$, where λ measures the degree of informational complexity of the assets. In the main model, we have proved that $\frac{\partial^2 \alpha}{\partial \pi^2} > 0$ holds for both the demand and the supply curve when η is small enough. Following the same logic, in this extension, $\frac{\partial^2 \alpha}{\partial \pi \partial \lambda} > 0$ for both the demand and the supply curve when η is small enough. This implies that the effects of lenders' sectorial experience obtained above will be larger the higher the value of λ.

A.6 Participants' experience

In this subsection we relax the assumption that $\pi_p = 1/2$. Instead, we allow for $1/2 \leq \pi_p < \pi$ and show that the main results still hold.

Asset prices. Similar to the main model, we solve for the asset resale price in the two sub-markets,

$$p_H = \overline{L} - 2\eta(1-\mu)A\left[\pi_p(1-\alpha) + \pi\alpha\right]$$

and

$$p_L = \underline{L} - 2\eta(1-\mu)A\left[(1-\pi_p)(1-\alpha) + (1-\pi)\alpha\right].$$

Then, the revenue per unit of assets that a lead lender expects to obtain in the asset liquidation market is

$$p_{lead} = \pi p_H + (1-\pi)p_L = \widetilde{L} - 2\eta(1-\mu)A\Big\{(1 - \pi_p - \pi + 2\pi_p\pi)(1-\alpha) + \left[\pi^2 + (1-\pi)^2\right]\alpha\Big\}.$$

Similar to the main model,

$$\frac{\partial p_{lead}}{\partial \alpha} = -2\eta(1-\mu)A(2\pi - 1)(\pi - \pi_p) < 0;$$

$$\frac{\partial p_{lead}}{\partial \pi} = (\overline{L} - \underline{L}) - 2\eta(1-\mu)A\left[(2\pi_p - 1)(1-\alpha) + (4\pi - 2)\alpha\right].$$

$\frac{\partial p_{lead}}{\partial \pi} > 0$ if and only if

$$\eta < \frac{\overline{L} - \underline{L}}{2(1-\mu)A\left[(2\pi_p - 1)(1-\alpha) + (4\pi - 2)\alpha\right]}.$$

The revenue per unit of assets that a participant expects to obtain in the asset liquidation market is

$$p_{par} = \pi_p p_H + (1-\pi_p)p_L = \widetilde{L}_p - 2\eta(1-\mu)A\left\{\left[\pi_p^2 + (1-\pi_p)^2\right](1-\alpha) + (1-\pi_p-\pi+2\pi_p\pi)\alpha\right\},$$

where $\tilde{L}_p = \pi_p \bar{L} + (1-\pi_p)\underline{L}$. We can show that

$$\frac{\partial p_{par}}{\partial \alpha} = 2\eta(1-\mu)A(2\pi_p - 1)(\pi - \pi_p) \geq 0,$$

and that

$$\frac{\partial p_{par}}{\partial \pi} = -2\eta(1-\mu)A(2\pi_p - 1)\alpha \leq 0.$$

Optimal monitoring. The optimal μ is again solved from the first order condition $\alpha\left(R - p_{lead}A\right) - c(\Omega)\mu = 0$ and the definition of p_{lead}. Analogously to the main model, we can show that μ is increasing in α and c. It is also decreasing in π when η is small enough.

Demand of lead share. The demand is solved from

$$F(\alpha) = \mu R + p_{par}(1-\mu)A - 1 = 0.$$

We can show that

$$\begin{aligned}
\frac{\partial F}{\partial \alpha} &= \frac{\partial \mu}{\partial \alpha}\left[R - p_{par}A + (1-\mu)A\frac{\partial p_{par}}{\partial \mu}\right] + (1-\mu)A\frac{\partial p_{par}}{\partial \alpha} > 0 \\
\frac{\partial F}{\partial \pi} &= \frac{\partial \mu}{\partial \pi}\left[R - p_{par}A + (1-\mu)A\frac{\partial p_{par}}{\partial \mu}\right] + (1-\mu)A\frac{\partial p_{par}}{\partial \pi} < 0.
\end{aligned}$$

Therefore $\frac{\partial \alpha}{\partial \pi} > 0$, i.e., a higher π shifts the demand curve to the right. The remaining characterizations of the demand side stay the same as in the main model.

Supply of lead share. The characterizations of the supply side are analogous to the main model.

A.7 Lending technologies: scenario with two borrower categories

In this appendix section, we consider an extension with two borrower categories characterized by different reliance on asset-based lending. The two borrower types have different value of assets, A_1 and A_2 with $A_1 < A_2$. Each group has a measure of $1/2$.

Asset prices. The demand of liquidated assets in both types of markets remain the same as in the main model. The supply of liquidated assets in the high market in turn reads

$$\frac{M}{4}\left[(1-\alpha_1)(1-\mu_1)A_1+(1-\alpha_2)(1-\mu_2)A_2\right]+\frac{\pi M}{2}\left[\alpha_1(1-\mu_1)A_1+\alpha_2(1-\mu_2)A_2\right],$$

where μ_i and α_i are the monitoring effort and the share of loan retained by a lead lender lending to a type-i borrower, $i \in \{1,2\}$. Equalizing asset demand and supply, we can solve for the asset price in the high market

$$p_H=\bar{L}-\eta\left\{\frac{1}{2}\left[(1-\alpha_1)(1-\mu_1)A_1+(1-\alpha_2)(1-\mu_2)A_2\right]+\pi\left[\alpha_1(1-\mu_1)A_1+\alpha_2(1-\mu_2)A_2\right]\right\}.$$

Similarly, the asset price in the low market is

$$p_L=\underline{L}-\eta\left\{\frac{1}{2}\left[(1-\alpha_1)(1-\mu_1)A_1+(1-\alpha_2)(1-\mu_2)A_2\right]+(1-\pi)\left[\alpha_1(1-\mu_1)A_1+\alpha_2(1-\mu_2)A_2\right]\right\}.$$

The revenue per unit of assets (p_{lead}) that a lead lender expects to obtain in the asset liquidation market is

$$\begin{aligned} p_{lead} &= \pi p_H+(1-\pi)p_L \\ &= \widetilde{L}-\eta\left\{\frac{1}{2}\left[(1-\alpha_1)(1-\mu_1)A_1+(1-\alpha_2)(1-\mu_2)A_2\right]\right. \\ &\quad \left.+\left[\pi^2+(1-\pi)^2\right]\left[\alpha_1(1-\mu_1)A_1+\alpha_2(1-\mu_2)A_2\right]\right\}. \end{aligned}$$

It is straightforward to show that p_{lead} is increasing in μ_1 and μ_2 and decreasing in α_1 and α_2. It is increasing in π if and only if

$$\eta<\frac{\bar{L}-\underline{L}}{(4\pi-2)\left[\alpha_1(1-\mu_1)A_1+\alpha_2(1-\mu_2)A_2\right]}.$$

Optimal monitoring. A lead lender that lends to a borrower of type i solves the problem

$$\max_{\mu_i}\left\{\alpha_i\mu_i R+\alpha_i(1-\mu_i)p_{lead}A_i-\frac{c(\Omega)\mu_i^2}{2}-\phi(\alpha_i)+\chi\right\}. \tag{24}$$

from which we obtain the first order condition

$$\alpha_i\left(R-p_{lead}A_i\right)-c(\Omega)\mu_i=0. \tag{25}$$

μ_1 and μ_2 can be solved by combining the two first order conditions and the definition of p_{lead}.

Demand of lead shares. The demand of lead share from type-i borrower is solved from

$$F_i(\alpha_i)=\mu_i R+(1-\mu_i)p_{par}A_i-1=0,$$

where

$$p_{par}=\frac{1}{2}\left(p_H+p_L\right)=\frac{1}{2}\left(\bar{L}+\underline{L}\right)-\frac{1}{2}\eta\left[(1-\mu_1)A_1+(1-\mu_2)A_2\right].$$

Supply of lead shares. The supply of lead share is solved from the participation constraint of the lead lender who lends to a type-i borrower:

$$U_i(\alpha_i) = \alpha_i \mu_i R + \alpha_i (1-\mu_i) p_{lead} A_i - \frac{c(\Omega)\mu_i^2}{2} - \phi(\alpha_i) + \chi = 0.$$

The special case of $\eta = 0$. When $\eta = 0$, the demand of liquidated assets is perfectly elastic, and the prices of liquidated assets do not depend on the quantity of assets liquidated. In other words, $p_{lead} = \tilde{L}$ and $p_{par} = \frac{1}{2}\left(\bar{L} + \underline{L}\right)$. In the main model (see Appendix A.2 and A.3) we have shown that $\frac{\partial^2 \alpha}{\partial \pi \partial A} > 0$ holds for the demand and supply curves under some parametric conditions when $\eta = 0$. Following the same steps, we can show here that $\frac{\partial \alpha}{\partial \pi}|_{A=A_1} < \frac{\partial \alpha}{\partial \pi}|_{A=A_2}$ for both the demand and the supply curve in this extended model. In other words, after an increase in π, the increase in lead share α_1 is smaller than the increase in α_2. By continuity, this holds in the neighborhood of $\eta = 0$.

A.8 Welfare

The policy maker takes as given the determination of the equilibrium in the asset liquidation market and in the syndicated loan market (thus, for given monitoring μ, he takes as given the choices of α and R). We posit that the policy maker can implement the desired optimal μ_p by imposing a tax or giving a transfer τ to lenders in case of asset liquidation (in fact, this will affect lead lenders' monitoring choice). Formally, the policy maker would maximize[33]

$$\begin{aligned}
\max_{\tau} W \quad &= \quad \mu_p R_p + (1-\mu_p)V - \frac{c\mu_p^2}{2} + (Y - R_p)\,\mu_p \\
&\qquad s.t. \quad \max_{\mu_p} \left\{ \alpha_p \mu_p R_p + \alpha_p (1-\mu_p)(p_{lead,p} - \tau) A - \frac{c(\Omega)\mu_p^2}{2} - \phi(\alpha_p) + \chi \right\}.
\end{aligned}$$

Thus, the policy maker maximizes total welfare, given by the total return of all lenders plus the total return of all borrowers. For simplicity, we posit that the risk premium $\phi(\alpha_p)$ is a transfer at the level of the economy. V is the average productivity of all liquidate assets

$$V = \frac{1}{1-\mu_p}\left[\frac{1}{4\eta}\left(\overline{L}^2 + \underline{L}^2 - p_{H,p}^2 - p_{L,p}^2\right)\right].$$

The optimal choice of μ_p on the part of the policy maker (and hence the optimal choice of the tax or transfer τ) would satisfy

$$Y - c\mu_p - V + (1-\mu_p)\frac{\partial V}{\partial \mu_p} = 0,$$

from which

$$\mu_p \quad = \quad \frac{Y - V + \frac{\partial V}{\partial \mu_p}}{c + \frac{\partial V}{\partial \mu_p}}.$$

[33] Note that in deriving equation (18), we focus on a scenario with a degenerate distribution $F(Y)$ of firms' output over the relevant region.

In comparison, in the decentralized equilibrium,

$$\mu = \frac{\alpha\left(R - p_{lead}A\right)}{c}.$$

The difference between μ_p and μ can be decomposed to three components.

$$\mu_p - \mu = \frac{\overbrace{-c\alpha[(V - p_{lead})A - (Y - R)]}^{W_1 \gtrless 0} + \overbrace{c(1-\alpha)(Y - VA)}^{W_2 > 0} + \overbrace{\frac{\partial V}{\partial \mu}\left[c - \alpha\left(R - p_{lead}A\right)\right]A}^{W_3 > 0}}{\underbrace{c\left(c + \frac{\partial V}{\partial \mu}A\right)}_{>0}}. \tag{26}$$

The policy maker's monitoring tends to be larger than the decentralized one for two reasons. The policy maker accounts for the return of all the lenders and borrowers, not only of the lead lenders (term W_2 in the numerator of the above equation). The policy maker also accounts for the fact that, if monitoring is higher, there will be fewer assets liquidated and the average productivity V of liquidated assets will be higher (this pecuniary externality is captured by the term W_3 in the numerator). A third force (the term W_1 in the numerator) is ambiguous. The policy maker accounts for the fact that liquidated assets may have an average productivity, V, larger than the resale price expected by lead lenders, p_{lead}. Hence, in this dimension the policy maker may tend to choose lower monitoring than what implied by the decentralized equilibrium. This is captured by the term A in the numerator.

A numerical example. To further illustrate the welfare properties of our equilibrium, we provide a simple numerical example. We assume the cost function $\phi(\alpha)$ takes the form $\phi(\alpha) = \psi[(1+\alpha)^n - 1]$. Table A.1 shows the parameter values used in this example.

The monitoring in the decentralized equilibrium (μ) and the policy maker's problem (μ_p) are 0.52 and 0.82, respectively. Therefore, the decentralized equilibrium features under-monitoring. The three factors W_1, W_2, and W_3 that contribute to the difference $\mu_p - \mu$ are all positive and explain 22%, 56% and 22% of the difference between μ_p and μ, respectively. For a wide range of parameters that we have experimented with, $\mu_p - \mu$ always remains positive, although the contributing factor W_1 sometimes turns negative.

Figure A.1 presents how the lead share α and welfare in the decentralized equilibrium varies for different levels of sectorial experience π. Consistent with our theoretical results, more sectorial experience π increases the lead share in the equilibrium. It also raises the welfare of the economy.

Parameter	Symbol	Value
Highest liquidation value in the high market	$\overline{L}$	1.00
Highest liquidation value in the low market	$\underline{L}$	0.80
Sectorial experience	π	0.80
Output of firms	Y	1.20
Units of liquidated assets	A	1.00
Elasticity of asset demand	η	0.10
Cost of monitoring	c	0.35
Loan origination fee	χ	0.15
Parameter in the origination cost function	ψ	0.20
Parameter in the origination cost function	n	3.00

Table A.1: Parameters

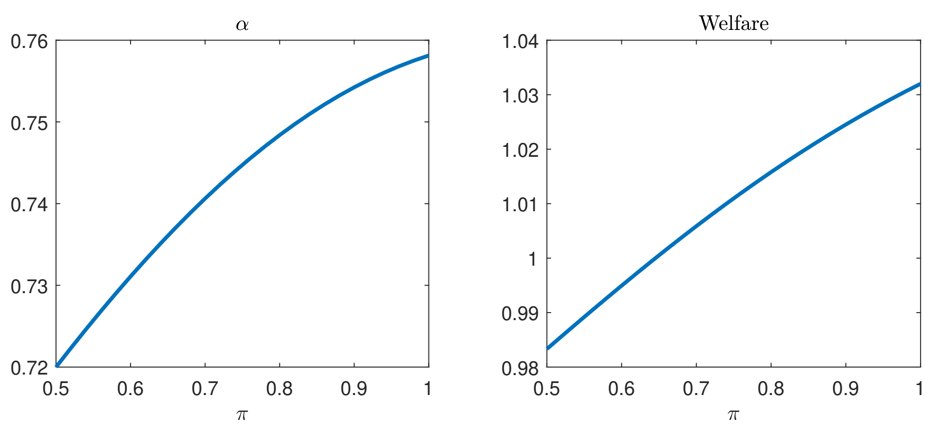


Figure A.1: The effect of sectorial experiences on decentralized equilibrium outcome.

Appendix B Additional Empirical Results

Table B.1: Correlation matrix

	(1)	(2)	(3)
(1) Sectoral experience (SIC2)	1		
(2) Firm experience (# loans)	-0.021***	1	
(3) Co-lending experience (# loans)	-0.027***	0.046***	1

This table presents the correlation matrix for the key variables used in the analysis. All variables are defined in Table 1. ***, **, and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Table B.2: Experience and firm heterogeneity

	I	II	III	IV	V	VI	VII	VIII
Sub-sample:	Tobin's q				External debt			
Dependent variable:	Prob(lead)		Lead shares(%)		Prob(lead)		Lead shares(%)	
Group:	Low	High	Low	High	Low	High	Low	High
Sector experience (SIC2)	0.280***	0.175***	32.335***	17.252*	0.264***	0.167***	32.841***	25.304*
	[6.515]	[3.952]	[2.748]	[1.715]	[4.975]	[3.444]	[3.543]	[1.837]
Firm experience (# loans)	0.150***	0.180***	-1.068***	-0.808***	0.158***	0.173***	-0.658**	-1.689***
	[19.971]	[28.759]	[-3.275]	[-3.086]	[21.957]	[23.263]	[-2.487]	[-6.221]
Co-lending experience (# loans)	0.020***	0.018***	-0.742**	-0.610**	0.021***	0.019***	-0.681***	-0.598**
	[4.333]	[5.156]	[-2.360]	[-2.376]	[5.403]	[4.819]	[-2.696]	[-2.332]
Chow test (P-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Loan controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	24,063	33,673	4,775	7,200	25,145	23,134	5,187	4,242
R-squared	0.550	0.556	0.792	0.782	0.571	0.557	0.826	0.777
Bank*Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry (SIC3)*Year*Rating FE	Y	Y	Y	Y	Y	Y	Y	Y
Clustered standard errors	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

The table reports coefficients and t-statistics (in brackets). We estimate the regression:

$$Y_{b,f,s,t} = \alpha^{'} + \lambda_1 Sector_{b,s,t}^{Exper} + \lambda_2 Firm_{b,f,t}^{Exper} + \lambda_3 Co-lending_{b,t}^{Exper} + \beta_1 L_{b,t} + \beta_2 F_{f,t-1} + \epsilon_{b,f,s,t}$$

where b, f, s, t refer to bank, firm, sector, and year, respectively. We estimate the regression on a loan-level sample originated from 1987 to 2014. The dependent variable is defined in the second row. In columns I-IV, we consider the firm's Tobin's q and split the sample into low and high groups if the firm's Tobin's q is below or above the mean, respectively. In columns V-VIII we do the same for the firm's external debt level. We also report p-values of a Chow test of differences in the experience estimated coefficients between the sub-groups under the null of $H_0 : \widehat{\beta}^{Low} = \widehat{\beta}^{High}$. All variables are defined in Table 1. All specifications include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity and the following loan and firm control variables: $Maturity$, $Collateral$, $Term$, $General\ covenants$, $Performance\ pricing$, $Tobin's\ q$, ROA, and $Firm\ size$. Standard errors are robust and clustered at the bank level. The *,**,*** marks denote the statistical significance at the 10, 5, and 1% level, respectively.

Table B.3: Experience and asset-based lending

	I
Dependent variable	Lead shares (%)
Sectoral experience (SIC2)	10.745***
	[3.184]
Firm experience (# loans)	-0.960*
	[-1.942]
Co-lending experience (# loans)	-2.863***
	[-7.191]
Sectoral experience (SIC2) * Asset-based lending	5.986*
	[1.660]
Firm experience (# loans) * Asset-based lending	-0.055
	[-0.113]
Co-lending experience (# loans) * Asset-based lending	2.183***
	[4.539]
Loan controls	Y
Bank controls	Y
Firm Controls	Y
Observations	16,900
R-squarred	0.678
Industry (SIC3)*Year FE	Y
Bank FE	Y
Clustered standard errors	Bank

The table reports coefficients and t-statistics (in brackets). We estimate the regression:

$$Y_{b,f,s,t} = \alpha^{'} + \lambda_1 Sector^{Exper}_{b,s,t} + \lambda_2 Firm^{Exper}_{b,f,t} + \lambda_3 Co{-}lending^{Exper}_{b,t} + \beta_1 L_{b,t} + \beta_2 F_{f,t-1} + \epsilon_{b,f,s,t}$$

where b, f, s, t refer to bank, firm, sector, and year, respectively. The dependent variable is the lead lender shares (%), reported in the first line. The table presents the main effects of sectoral, firm, and co-lending experience and their interactions with $asset-based\ lending$. $Asset-based\ lending$ is defined as a dummy variable equal to one when a bank's relative amount of loans backed by collateral over the past five years exceeds the sample mean (0.31), capturing the bank's tendency towards collateral-based lending. We estimate the regression on a loan-level sample originated from 1987 to 2014. All variables are defined in Table 1. All specifications include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity and the following loan, bank and firm control variables: $Maturity$, $Collateral$, $Term$, $General\ covenants$, $Performance\ pricing$, $Bank\ size$, $NPLs$, $Deposits$, $Tobin's\ q$, ROA, and $Firm\ size$. Standard errors are robust and clustered at the bank level. The *,**,*** marks denote the statistical significance at the 10, 5, and 1% level, respectively.

Table B.4: Aggregate lending in the commercial market and enforcement actions

	I	II
Dependent variable:	Total loans	Total loans
Enforcement	-0.044***	-0.030***
	[-6.742]	[-4.070]
Deposits		0.276***
		[2.942]
Tier1		-0.267***
		[-3.024]
NPLs		-0.985**
		[-2.453]
HHI-deposits		3.687**
		[2.551]
Observations	30,857	26,444
R-squared	0.844	0.903
Year FE	Y	Y
Bank FE	Y	Y
Clustered standard errors	Bank	Bank

The table reports coefficients and t-statistics (in brackets). We estimate the regression:

$$Y_{b,t} = \beta_1 Enforcement_{b,t-1} + \beta_2 B_{b,t-1} + \alpha_b + \alpha_t + \epsilon_{b,t}$$

where b refers to bank and t years. $Enforcement_{b,t}$ is a dummy equal to one when a bank receives a regulatory enforcement action. The dependent variable is the total loans in the commercial market over total assets. We estimate the regression on a bank-quarter sample originated from 1999 to 2011. All variables are defined in Table 1. All specifications include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. Standard errors are robust and clustered by bank. The *,**,*** marks denote the statistical significance at the 10, 5, and 1% level, respectively.

Table B.5: Treatment group for post sanction members: Class 1

	I	II	III	IV
Dependent variable	Prob(Lead)		Lead shares (%)	
Sector experience (SIC2)	0.188***	0.115***	11.780	16.453***
	[5.668]	[4.204]	[0.652]	[3.663]
Firm experience (# loans)	0.147***	0.124***	-0.276	-0.285
	[10.187]	[10.304]	[-0.803]	[-1.122]
Co-lending experience (# loans)	0.021***	0.019***	-0.004	-0.920***
	[5.480]	[6.179]	[-0.029]	[-2.989]
Sanction (Class 1) * Sectoral experience (SIC2)	0.327***	0.240***	29.369***	20.943***
	[9.823]	[9.556]	[11.580]	[6.009]
Sanction (Class 1) * Firm experience (# loans)	-0.028**	-0.021**	-0.933**	0.319
	[-2.229]	[-2.050]	[-2.033]	[1.035]
Sanction (Class 1) * Co-lending experience (# loans)	0.511***	0.297***	-1.073***	-0.925***
	[5.970]	[33.505]	[-3.242]	[-3.600]
Loan controls	Y	Y	Y	Y
Firm controls	Y	Y	Y	Y
Post-sanction variable		Y		Y
Observations	27,337	25,330	5,237	5,776
R-squarred	0.609	0.639	0.798	0.773
Year FE		Y		Y
Industry (SIC3)*Year FE	Y		Y	
Bank*Year FE	Y		Y	
Bank*Industry (SIC3) FE		Y		Y
Clustered standard errors	Bank	Bank	Bank	Bank

The table reports coefficients and t-statistics (in brackets). We estimate the regression:

$$Y_{b,f,s,t} = \alpha^{'} + \lambda_1 Sector^{Exper}_{b,s,t} + \lambda_2 Firm^{Exper}_{b,f,t} + \lambda_3 Co-lending^{Exper}_{b,t} + \beta_1 L_{b,t} + \beta_2 F_{f,t-1} + \epsilon_{b,f,s,t}$$

where b, f, s, t refer to bank, firm, sector, and year, respectively. $Sanction$ (Class 1) is a dummy variable equal to one when an enforcement action is related to key principles, focusing on maintaining adequate capital (Basel principle 16), ensuring the quality of assets (Basel principle 18), and managing loan loss provisions and exposures (Basel principle 19-20). These actions are essential for upholding banking institutions' safety and financial integrity. We estimate the regression on a loan-level sample originated from 1999 to 2011 due to the sanctions data coverage. The dependent variable is reported in the first line. All variables are defined in Table 1. All specifications include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity and the following loan and firm control variables: $Maturity$, $Collateral$, $Term$, $General\ covenants$, $Performance\ pricing$, $Tobin's\ q$, ROA, and $Firm\ size$. Standard errors are robust and clustered at the bank level. The *,**,*** marks denote the statistical significance at the 10, 5, and 1% level, respectively.

Table B.6: Firm experience and lead lender shares (%): Alternative definitions

	I	II	III	IV	V	VI
Dependent variable:	Prob(lead)	Lead shares (%)	Prob(lead)	Lead shares (%)	Prob(lead)	Lead shares (%)
Category:	Duration		# loans - 6 years		Relationship lending	
Sector experience (SIC2)	0.184***	21.695***	0.223***	22.640***	0.207***	21.514***
	[4.986]	[2.963]	[6.127]	[3.019]	[7.079]	[2.896]
Firm experience - category	0.009***	-0.573***	0.036***	-0.766***	0.602***	-4.647***
	[7.478]	[-6.049]	[9.002]	[-2.930]	[29.381]	[-7.061]
Co-lending experience (# loans)	0.022***	-0.676**	0.023***	-0.703**	0.017***	-0.706**
	[4.987]	[-2.485]	[4.836]	[-2.405]	[4.544]	[-2.413]
Loan controls	Y	Y	Y	Y	Y	Y
Bank controls	Y	Y	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y	Y	Y
Observations	59,262	14,067	59,262	14,067	59,262	14,067
R-squared	0.325	0.625	0.325	0.625	0.325	0.625
Industry (SIC3)*Year*Rating FE	Y	Y	Y	Y		
Bank*Year FE	Y	Y	Y	Y		
Clustered standard errors	Bank	Bank	Bank	Bank	Bank	Bank

The table reports coefficients and t-statistics (in brackets). We estimate the regression:

$$Y_{b,f,s,t} = \alpha^{'} + \lambda_1 Sector^{Exper}_{b,s,t} + \lambda_2 Firm^{Exper}_{b,f,t} + \lambda_3 Co-lending^{Exper}_{b,t} + \beta_1 L_{b,t} + \beta_2 F_{f,t-1} + \epsilon_{b,f,s,t}$$

where b, f, s, t refer to bank, firm, sector, and year, respectively. The dependent variable is reported in the second row. *Duration* is the length of time the bank and firm have maintained a lending relationship. It is defined as the number of years between the first and last loan originated between a specific bank and firm pair in our sample. *# loans - 6 years* measures the number of loans from lender b to firm f in the last 6 years prior to the current loan. *Relationship lending* is a dummy variable equal to one if bank b lent to the same firm in the past five years and zero otherwise. All specifications include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity and the following loan and firm control variables: $Maturity$, $Collateral$, $Term$, $General\ covenants$, $Performance\ pricing$, $Tobin's\ q$, ROA, and $Firm\ size$. Standard errors are robust and clustered at the bank level. The *,**,*** marks denote the statistical significance at the 10, 5, and 1% level, respectively.

Table B.7: Sensitivity test for SIC sectors

	I	II	III	IV	V	VI
Dependent variable:	Lead bank			Lead shares (%)		
Sector experience (SIC1)	0.098***			9.163***		
	[3.959]			[2.771]		
Sector experience (SIC3)		0.222***			29.504***	
		[5.741]			[4.053]	
Sector experience (SIC4)			0.220***			34.532***
			[5.326]			[4.880]
Firm experience (# loans)	0.157***	0.156***	0.156***	-1.025***	-1.019***	-1.018***
	[17.933]	[17.871]	[17.874]	[-6.064]	[-5.941]	[-5.944]
Co-lending experience (# loans)	0.018***	0.018***	0.018***	-0.738**	-0.736**	-0.734**
	[4.572]	[4.584]	[4.584]	[-2.484]	[-2.478]	[-2.471]
Loan controls	Y	Y	Y	Y	Y	Y
Firm controls	Y	Y	Y	Y	Y	Y
Observations	60,148	60,148	60,148	16,101	16,101	16,101
R-squared	0.489	0.489	0.489	0.702	0.703	0.704
F-test	157.7	153	154	138	145.3	148.4
Industry (SIC3)*Year*Rating FE	Y	Y	Y	Y	Y	Y
Bank*Year FE	Y	Y	Y	Y	Y	Y
Clustered standard errors	Bank	Bank	Bank	Bank	Bank	Bank

The table reports coefficients and t-statistics (in brackets). We estimate the regression:

$$Y_{b,f,s,t} = \alpha' + \lambda_1 Sector^{Exper}_{b,s,t} + \lambda_2 Firm^{Exper}_{b,f,t} + \lambda_3 Co-lending^{Exper}_{b,t} + \beta_1 L_{b,t} + \beta_2 F_{f,t-1} + \epsilon_{b,f,s,t}$$

where b, f, s, t refer to bank, firm, sector, and year, respectively. We estimate the regression on a loan-level sample originated from 1987 to 2014. The dependent variable is reported in the second line. All variables are defined in Table 1. All specifications include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity and the following loan and firm control variables: $Maturity$, $Collateral$, $Term$, $General\ covenants$, $Performance\ pricing$, $Tobin's\ q$, ROA, and $Firm\ size$. Standard errors are robust and clustered at the bank level. The *,**,*** marks denote the statistical significance at the 10, 5, and 1% level, respectively.

Table B.8: Experience and nonlinearities

	I	II	III	IV
Dependent variable:	Lead bank		Lead shares (%)	
Sector experience (SIC2)	0.561***	0.330***	51.966***	65.716***
	[7.584]	[5.392]	[4.354]	[5.758]
Sector experience (SIC2)^2	-0.594***	-0.263***	-46.848***	-53.928***
	[-6.820]	[-4.364]	[-3.078]	[-4.481]
Firm experience (# loans)	0.231***	0.198***	-1.632***	-0.757***
	[16.837]	[16.928]	[-6.556]	[-6.049]
Firm experience (# loans)^2	-0.010***	-0.008***	0.078**	0.027
	[-4.791]	[-4.043]	[2.467]	[1.359]
Co-lending experience (# loans)	0.035***	0.029***	-2.458***	-2.038***
	[6.262]	[6.394]	[-4.382]	[-4.566]
Co-lending experience (# loans)^2	-0.001***	-0.000***	0.043***	0.035***
	[-4.002]	[-4.022]	[3.657]	[3.566]
Loan controls	Y	Y	Y	Y
Firm controls	Y	Y	Y	Y
Observations	60,148	56,060	16,101	16,144
R-squarred	0.519	0.560	0.713	0.689
Year FE	N	Y	N	Y
Bank*Year FE	Y	N	Y	N
Industry (SIC3)*Year FE	Y	N	Y	N
Bank*Industry (SIC3) FE	N	Y	N	Y
Clustered standard errors	Bank	Bank	Bank	Bank

The table reports coefficients and t-statistics (in brackets). We estimate the regression:

$$Y_{b,f,s,t} = \alpha' + \lambda_1 * Sector^{Exper}_{b,s,t} + \lambda_2 * Firm^{Exper}_{b,f,t} + \lambda_3 * Co-lending^{Exper}_{b,t} + \beta_1 * L_{l,t} + \beta_2 * F_{f,t-1} + \epsilon_{b,f,s,t}$$

where b, f, s, t refer to bank, firm, sector, and year, respectively. The dependent variable is reported in the second line. All variables are defined in Table 1. All specifications include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity and the following loan and firm control variables: $Maturity$, $Collateral$, $Term$, $General\ covenants$, $Performance\ pricing$, $Tobin's\ q$, ROA, and $Firm\ size$. Standard errors are robust and clustered at the bank level. The *,**,*** marks denote the statistical significance at the 10, 5, and 1% level, respectively.