Banking on Experience. Capital Reallocation, Asset Knowledge, and the Structure of Lending Contracts *

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Abstract

The corporate sector continuously engages in the reallocation of physical capital. We study the implications for corporate lending outcomes of a novel channel of bank experience, capital allocation engagement. Using U.S. loan-level data matched with firm-level data on capital asset transactions, we construct a measure of bank experience on capital reallocation. We find that, while experience on firms and co-lenders reinforces banks' monitoring incentives, capital allocation engagement dilutes them, calling for larger involvement in lending syndicates. We interpret these findings through a syndication model in which banks' experience about the reallocation opportunities of physical capital raises liquidation values after loan defaults, diluting monitoring incentives.

Keywords: Banks, Experience, Capital Allocation, Sector Specialization, Monitoring

JEL Classification: G21, D8

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*We thank the editor and an anonymous referee for their comments, as well as Rajkamal Iyer, Amiyatosh Purnanandam, Uday Rajan, Enrico Sette and Youngsuk Yook for helpful comments and conversations. We are also grateful to seminar participants at Bank of Italy, Luiss Business School (Rome), Michigan State University, University of Glasgow, University of Essex, University of Naples (Center for Studies in Economics and Finance), University of Sheffield, and conference participants at MMF (Cambridge), Bristol Banking Workshop, and Swiss Winter Conference (CEPR) on Financial Intermediation. All errors are our responsibility.

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Abstract

The corporate sector continuously engages in the reallocation of physical capital. We study the implications for corporate lending outcomes of a novel channel of bank experience, capital allocation engagement. Using U.S. loan-level data matched with firm-level data on capital asset transactions, we construct a measure of bank experience on capital reallocation. We find that, while experience on firms and co-lenders reinforces banks' monitoring incentives, capital allocation engagement dilutes them, calling for larger involvement in lending syndicates. We interpret these findings through a syndication model in which banks' experience about the reallocation opportunities of physical capital raises liquidation values after loan defaults, diluting monitoring incentives.

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1 Introduction

Lenders acquire information about a firm and its industry to make lending decisions. Information collection has been captured through repeated bank-firm interactions (i.e., relationship lending) and a bank's lending concentration towards a given industry (i.e., industry specialization). Previous literature showed that relationship lending increases the likelihood of being chosen as lead arranger in lending consortia and impacts lending conditions (e.g., Sufi, 2007; Bharath, Dahiya, Saunders and Srinivasan, 2011; Chodorow-Reich, 2014). Industry specialization allows lenders to enjoy informational advantages in the borrower's market (e.g., De Jonghe, Dewachter, Mulier, Ongena and Schepens, 2020; Blickle, Parlatore and Saunders, 2023; Paravisini, Rappoport and Schnabl, 2023).

In this paper, we model and empirically show the relevance for lending outcomes of a novel *capital allocation engagement* channel, where banks accumulate experience about firms holding and retrading similar capital assets in the industry in which a borrower is active. Our analysis builds on the literature that highlights the fundamental role of the reallocation process of firms' physical capital, that is, the continuous process through which firms liquidate, resell and acquire capital assets in secondary asset markets (see, e.g., Eisfeldt and Rampini, 2006; Eisfeldt and Shi, 2018, and references therein). The reallocation of capital assets in secondary markets is intense (Gavazza, 2011; Pulvino, 1998). Moreover, sectors exhibit substantial dispersion in the intensity of capital reallocation. Our data based on U.S. firms active in the syndicated loan market show an interquartile range variation across sectors of $4 billion in our measure of capital reallocation. Previous studies show that banks routinely accumulate experience on the best second-hand users of collateral assets and on the most suitable liquidation strategies of physical capital (Habib and Johnsen, 1999). Our inquiry is especially inspired by Cui, Wright and Zhu (2024), who model firms' capital reallocation following idiosyncratic shocks employing a setting where secondary market asset reallocation incurs liquidity, search and bargaining frictions.

Capital allocation engagement captures a bank's experience with a firm's capital reallocation opportunities in the industry in which the firm is active. In particular, it measures the bank's sectorial concentration with firms that actively manage (retrade) their physical capital within a specific industry. We argue that banks with greater experience about the (re)allocation of capital assets in an industry have an informational advantage in liquidating or selling capital assets pledged as collateral. This kind of experience differs from industry specialization as it captures variation in the underlying industry characteristics regarding asset liquidity that go beyond simple exposure measures to that industry.

In our analysis, we focus on the implications for lending arrangements of our novel channel of banks' credit market experience (*capital allocation engagement*) while controlling for already established sources of bank experience. In particular, we detect strikingly different effects of *capital allocation engagement* from widely studied forms of bank-firm experience (relationship lending), industry specialization, and from bank experience that relates to a bank's interactions with its peers (co-lending experience).[1]

We use the syndicated loan market as a testing ground for studying how the different forms of credit market experience affect lending outcomes, firms' behavior, and banks' behavior vis-à-vis other syndicate members. The syndicated loan market is well suited for our purposes as over the course of repeated, frequent interactions in lending consortia, syndicate members learn from the actions and decisions of other syndicate members and garner valuable experience on firms and the sectors they operate in.[2] In particular, 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.

The matched data set enables us to construct our novel measure of bank experience (*capital allocation engagement*) while controlling for previously employed indicators of relationship lending and industry specialization. *Capital allocation engagement* captures a bank's experience about the reallocation of physical capital in the sector in which the firm

[1]Co-lending experience captures the degree of learning from prior interactions with other banks over the course of syndicated loans. Co-lending experience can be obsolete due to misbehavior of the co-lending parties. We employ bank sanctions to capture a downgrade in such co-lending experience.

[2]As we elaborate below, the syndicate 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.

[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 are almost entirely sold off in the secondary market.

is active at a particular point in time. It measures the capital asset turnover (sales of property, plant and equipment, acquisitions and capital expenditures) for each firm a bank is lending to in a particular sector (weighted by its loan exposure to firms in that sector) relative to the overall capital asset turnover in that sector. Banks with greater capital allocation engagement learn more about secondary market trading in the sector.

We first ask our data whether banks in loan syndicates actively learn through capital allocation engagement and whether this determines participation in loan syndicates at the extensive margin. We find a positive impact of capital allocation engagement on the probability of a bank being selected as a lead arranger, while controlling for a variety of loan, borrower, and bank characteristics: a one-standard-deviation increase in capital allocation engagement raises the probability of being a lead arranger by approximately 3 percentage points.

We then investigate to what extent bank experience about the (re)allocation of physical capital attenuates or amplifies 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 hazard in a syndicate: the higher 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 a nuanced impact of bank experience about capital (re)allocation: a one-standard-deviation increase in capital allocation engagement raises the lead share by almost 3.5 percentage points. This contrasts with the effects of co-lending experience and relationship lending: for instance, a one-standard-deviation increase in co-lending decreases the lead share by 1.8 percentage points. Thus, the estimates suggest that moral hazard within syndicates is more severe when the lead arranger has greater experience about the (re)allocation of capital assets in the sector. These results are obtained while controlling for credit supply and firm demand within an industry.

We rationalize the empirical findings through the lens of a theoretical model of loan syndication. In the model economy, lending banks accumulate experience on borrowing firms (i.e., relationship lending), co-lenders, and on the process of (re)allocation of physical capital in the sector of activity of borrowers. Relationship lending and co-lending experience facilitate syndicate arrangers' activity of loan monitoring. Experience about capital (re)allocation in the borrower's sector eases lenders' liquidation and redeployment of borrowers' capital assets among sector peers in the event of loan default. Through their capital allocation experience, in fact, lenders can more easily identify suitable capital asset buyers in the sector, and choose the most appropriate timing and location for asset liquidation. A lender with a stronger capital allocation engagement 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 retain a higher loan share. Overall, the theoretical model suggests that, while 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 learning about capital reallocation 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 *capital allocation engagement* are more pronounced in industries characterized by high informational complexity of products. Second, we exploit information on banks' reliance on asset-based lending. Consistent with the predictions of the theoretical model, the estimates suggest that the effect of a lender's capital allocation engagement is more pronounced for firms with a greater capital intensity, i.e., when firms' assets are relatively more important in loan contracts (i.e., lending is asset-based rather than cash-flow based). Third, we obtain that banks with higher *capital allocation engagement* tend to request fewer covenants in loan contracts, suggesting that they resort less to contractual restrictions and monitoring mechanisms, as they rely more on the ability to recover assets in the event of default.

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 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.

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 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. The reallocation of physical capital represents a fundamental component of corporate investment, restructuring and liquidation decisions (e.g., Eisfeldt and Rampini, 2006; Eisfeldt and Shi, 2018). To the best of our knowledge, this paper is the first to show how banks' experience regarding the process of capital (re)allocation within an industry affects outcomes in 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 borrowers over multiple interactions through relationship lending (Boot, 2000; Ongena and Smith, 2000; Gopalan, Udell and Yerramilli, 2011; Berger, Minnis and Sutherland, 2017), and that relationship lending affects lending allocation within the syndicated loan market (e.g. Sufi, 2007; Bharath et al., 2011; Chodorow-Reich, 2014). Similarly, credit allocation towards specific industries (industry specialization) allows lenders to enjoy informational advantages in the borrower's market and adjust loan contract terms (e.g. De Jonghe et al., 2020; Blickle et al., 2023; Paravisini et al., 2023). We shed light on a novel channel through which bank experience has an impact on credit arrangements.

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 capital allocation engagement, 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 asset allocation engagement, to sort out the ultimate impact on credit market outcomes.[4] To be clear, the key role that sectorial knowledge plays in commercial lending decisions has been recognized by scholarly studies (e.g. Paravisini et al., 2023) and more broadly by the banking community. In fact, 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

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

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.[5]

Finally, the paper relates to the literature that highlights the role of legal costs, bankruptcy quality, and collateral rules in determining the structure of corporate debt and lending contracts (see, e.g., Cerqueiro, Ongena and Roszbach, 2016; Calomiris, Larrain, Liberti and Sturgess, 2017; Haselmann, Pistor and Vig, 2010). Our paper provides insights to this literature by showing that the ultimate impact of legal frameworks and bankruptcy processes can depend on banks' experience on capital (re)allocation. In particular, the identified impacts of legal or bankruptcy reforms can be a joint estimate of the direct impact of a legal change and the countervailing indirect impact stemming from banks' capital allocation engagement. As such, previous estimates of the effect of legal changes may have been a lower bound as they overlooked the indirect effect through (changes in) banks' capital allocation engagement. Similarly, cross-country studies aiming to uncover the impact of legal heterogeneity may also draw biased inferences in case the indirect effect through banks' experience on capital reallocation differs across the captured legal variation (e.g., because of cross-country differences in secondary asset markets and in lenders' engagement in capital reallocation). Furthermore, while legal changes are insightful to identify the average impact, they forego studying the heterogeneity that stems from banks' experience on capital reallocation, as legal changes can affect banks' usage and experience of secondary asset markets to a significantly different degree. We extensively elaborate on the relationship with this literature later in the analysis, when discussing the empirical relevance of capital allocation engagement. In addition, we investigate the influence of capital allocation engagement on the effects of a legal reform through the lens of our model.

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. Sec-

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

tion 5 contains the main results. Section 6 presents further tests that dissect the scenarios in which bank experience has a stronger influence. Section 7 contains robustness tests. Section 8 concludes. Proofs of the model and additional theoretical and empirical results are relegated to the online appendix.

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 co-lenders naturally eases the activity of monitoring of the lead bank, incentivizing its monitoring, the experience of a lead bank about capital (re)allocation in the sector (*capital allocation engagement*) 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 A units of assets of the project can be rescued. λ ($\lambda < 1$) fraction of these assets can be resold in an asset liquidation market and reused by other firms, where λ captures the ability to participate in the secondary asset market (e.g. due to bankruptcy procedures and legal restrictions).

We model the reallocation of assets in a parsimonious way. Any active firm can purchase λA units of 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).[6]

Financing Firms have no initial endowment and, hence, need to obtain financing from lenders to implement projects.[7] 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

[6]In our model economy, all asset trades involve the sale and purchase of assets of liquidated firms. The model could be extended to allow for other secondary market asset transactions. This would not affect the mechanisms studied in the analysis.

[7]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 produces output instantaneously.

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 be able to repossess assets in proportion of their loan shares, obtaining $\alpha\lambda A$ and $(1-\alpha)\lambda A$, 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 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 previous 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 $c'(.) < 0$.

Capital assets liquidation In the event of project failure and loan default, each lender can resell the assets he repossessed in the liquidation market. 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 $\underline{L} < \overline{L} < 1/(\lambda A)$. 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 about capital (re)allocation in the sector. For example, such 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 (i.e., the lender's *capital allocation engagement*) 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.5 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 to 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.

Asset liquidation market Using the distribution of liquidation returns in (1) and (2), in the high market and in the low market the demand for liquidated assets is respectively given by

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

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

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

that is, it equals the supply of liquidated assets by participant lenders $(1/2)(1\text{-}\alpha)(1\text{-}\mu)\lambda A$ plus the asset supply of lead lenders $\pi\alpha(1-\mu)\lambda A$.[8] 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 experience about capital (re)allocation 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[9]

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

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

[9]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.

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

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

and

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

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:

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

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

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

which we assume henceforth. Intuitively, the direct benefit that their experience about capital (re)allocation 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.[10]

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

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

from which we obtain the first order condition

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

[10]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.

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 experience about capital (re)allocation, 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

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

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

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

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.[11]

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, experience about capital (re)allocation in the sector can make a lead arranger "lazy" by raising his expected

[11] 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.5, we also consider $\pi_p > \frac{1}{2}$.

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 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[12]

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

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.[13]

[12]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.

[13]Firm experience could also boost the liquidation value of assets. However, as long as this effect does not dominate the direct effect of firm experience in reducing the monitoring cost (through $c(\Omega)$), the

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 about capital (re)allocation can make the lead arranger "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 experience about capital (re)allocation in the sector 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 higher lead share occurs when banks' sectorial experience (*capital allocation engagement*) boosts banks' expected asset liquidation values in the event of borrowers' default;
ii) A lower lead share is more likely when banks' experience about borrowers and co-lenders eases monitoring activities.

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

substitutability result will hold.

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. 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 about capital (re)allocation 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 Extensions, Robustness, and Welfare

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

2.5.1 More on lenders' experience about capital reallocation

In this extension, we elaborate on the role of lenders' experience about capital (re)allocation. 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., the *capital allocation engagement* 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 informationally complex the assets, 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 experience about capital (re)allocation in the sector is given by $\psi\pi$, where ψ 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 ψ (see Appendix A.4 for details).[14]

Testable Hypothesis 3: A larger informational complexity of products tends to reinforce the effects of banks' sectorial experience about capital (re)allocation on loan contract terms.

2.5.2 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

[14] In the appendix we also study other variations of the specification of lenders' experience about capital reallocation. In Appendix A.5, we study a generalized case with participants' experience π_p different from 1/2. In Appendix A.6, we consider a variation of the model in which lenders' effort in acquiring experience about the asset liquidation market is endogenous.

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 collateral 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 greater 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 following statement 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 larger reliance on asset-based lending (higher A) reinforces the effects of lenders' sectorial *capital allocation engagement* on loan contract terms.

2.5.3 Robustness: delegated liquidation

The reader could wonder how the results would be affected if, after borrowers' default, participant lenders could partially re-hire lead 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 Nash bargaining over the rent associated with lead lenders' higher liquidation skills. Denoting by β the lead lender's bargaining power, the lead lender will expect to obtain

$$\beta(1-\alpha)(p_{lead}-p_{par})\lambda A \tag{18}$$

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

$$(1-\alpha)\left[(1-\beta)(p_{lead}-p_{par})+p_{par}\right]\lambda A=(1-\alpha)\left[(1-\beta)p_{lead}+\beta p_{par}\right]\lambda A. \tag{19}$$

The optimal monitoring of a lead lender will become

$$\mu=\frac{\alpha R-\left[\alpha p_{lead}+\beta(1-\alpha)(p_{lead}-p_{par})\right]\lambda A}{c}. \tag{20}$$

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, the results of the baseline set up would carry through. Appendix A.8 provides more details on this robustness analysis.

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.9 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 [15]

$$\mu_p - \mu = \frac{\overbrace{-c\alpha[(V - p_{lead})\lambda A - (Y - R)]}^{W_1 \gtreqless 0} + \overbrace{c(1-\alpha)(Y - V\lambda A)}^{W_2 > 0} + \overbrace{\frac{\partial V}{\partial \mu}\left[c - \alpha\left(R - p_{lead}\lambda A\right)\right]\lambda A}^{W_3 > 0}}{\underbrace{c\left(c + \frac{\partial V}{\partial \mu}\lambda A\right)}_{>0}}. \tag{21}$$

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 (21)). 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 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 about capital (re)allocation. In fact, if lenders' monitoring is suboptimally low in equilibrium, lenders' sectorial experience will have an ambiguous effect on welfare. On the one hand, *capital allocation engagement* 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 reallocations). If lenders' monitoring is instead suboptimally high in equilibrium ($\mu_P - \mu < 0$), lenders'

[15] Note that, in deriving equation (21), we focus on a scenario with a degenerate distribution $F(Y)$ of firms' output over the relevant region.

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.9. 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 about capital (re)allocation nevertheless exerts an overall positive effect on total welfare by significantly raising the average productivity of liquidated assets.

3 Empirical Analysis

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. Before delving into the empirical analysis, to understand the distinct nature of our empirical measure of lenders' experience about capital (re)allocation, we contrast it with measures of asset liquidity considered in previous empirical works. We then show how our capital allocation engagement measure can provide insights into the credit market consequences of phenomena and transformations that occurred in recent decades, including transformations of the secondary market for firm assets, bankruptcy and legal reforms, and credit market liberalizations.

3.1 The Empirical Relevance of Capital Allocation Engagement

Recall that in the theoretical model the value that a lead lender expects to obtain from the resale and liquidation of a borrowing firm's assets is given by

$$LiquidationValue = p_{lead}(\lambda, \pi)\lambda A \tag{22}$$

where, from the expression for p_{lead} in (8), $\partial p_{lead}/\partial \pi \geq 0$ and $\partial p_{lead}/\partial \lambda \leq 0$.

In (22), λ can be interpreted as the degree of asset liquidity and ease of asset repossession at the firm level driven, for example, by the quality of bankruptcy laws and liquidation procedures. As we elaborate below, easier bankruptcy procedures can reduce the legal and court costs that a lender must sustain to repossess assets, raising λ. In (22), π captures instead the experience about capital (re)allocation of a lender, as driven by the degree of engagement of the lender in secondary asset market transactions. For instance, in the micro-foundation presented in Section 2.5.1, this was determined by the number of transactions (N) in which a lender was previously involved in the secondary asset market. Our empirical setting keeps λ unaffected but aims to uncover the impact of heterogeneity in banks' secondary asset market experience π for a given level of asset liquidity and ease of repossession at the firm level (λ) stemming from the quality of bankruptcy and liquidation. In our empirical analysis, we will proxy π with the *capital allocation engagement* variable,

$$Capital\ allocation\ engagement_{b,s,t} = \frac{\sum_{f=1}^{F}(Asset\ transactions_{f,s,t} * Loan_{b,f,s,t})}{\sum_{b=1}^{B}\left(\sum_{f=1}^{F}(Asset\ transactions_{f,s,t} * Loan_{b,f,s,t})\right)}, \tag{23}$$

where $Asset\ transactions_{f,s,t}$ is the total of sales of property, plant, and equipment, acquisitions, and capital expenditures for each firm f in sector s at time t (Cui et al., 2024); $Loan_{b,f,s,t}$ denotes the credit (in millions of dollars) granted by bank b to firm f in sector s at time t; and F and B capture the total number of firms and banks, respectively. The bank-industry capital allocation engagement thus captures the participation of a bank in the secondary asset market transactions of a sector, relative to the overall intensity of transactions (turnover) in the secondary market of the sector. It ranges between zero and one, with higher values indicating higher engagement, and hence experience, of a bank in the asset market of a sector.

In what follows, we examine three relevant scenarios in which structural transformations or institutional reforms can affect π, λ or both: transformations of secondary asset markets and credit markets, and legal (bankruptcy) reforms. This further illustrates the distinct nature of our measure of capital allocation engagement (π) relative to previously used proxies for legal and bankruptcy quality (λ).

i) *Secondary Asset Market Transformations.* A scenario in which our measure of capital allocation engagement can help capture and predict changes in credit market behavior consists of structural transformations of secondary markets. Secondary asset markets are large: according to Waterston (1964) in the 1960s used machine tools accounted for more than two-thirds of the machine tools traded in the United States; Bond (1983) estimates that in the 1970s more than half of the trucks traded in the United States were sold in secondary markets; Gavazza (2011) reports that, since the mid-1980s, transactions in the secondary market for aircrafts have grown significantly and are now about three times the number of transactions involving new aircrafts. And the secondary markets for construction equipment, energy equipment, and medical equipment are also very active. Below, we will show that in our data the asset market turnover (the denominator of (23)) is large on average and exhibits substantial variation across sectors.

A broad literature documents the presence of frictions in secondary markets for firm assets[16] and that such frictions change over time due to technological and institutional transformations (see, e.g., Eisfeldt and Rampini, 2006; Ramey and Shapiro, 2001; Maksimovic and Phillips, 2001; Pulvino, 1998; Schlingemann, Stulz and Walkling, 2002). Mahone (2023) shows that the diffusion of online platforms (e.g., BIZBuySell) has affected the fluidity of secondary asset markets. Gavazza (2011) demonstrates that deregulation, and the resulting changes in the industry structure, increased turnover in the secondary market for used aircrafts. The increase in the importance of intermediaries has also contributed to a higher turnover in secondary asset markets. For example, in some industries the entry of specialized lessors in the mid-1980s led to an expansion of secondary market trade.

While the literature has studied the impact of secondary market transformations on productivity and capital accumulation (see, e.g., Foster, Haltiwanger and Syverson, 2008; Ramey and Shapiro, 1998), little is known about their influence on credit market behavior. Our analysis suggests that an increase of asset turnover in secondary markets induced by the above-mentioned transformations could alter the effect of lenders' capital allocation engagement on lenders' monitoring incentives.[17] In particular, using the expressions in (22) and (23), we can visualize the possible effect of the above secondary market transformations as an increase in the denominator of the capital allocation engagement measure (i.e., an

[16] As discussed by Gavazza (2011) and Pulvino (1998), in the secondary markets for aircrafts, for example, trading frictions are important. Aircrafts are traded in decentralized markets, through privately negotiated transactions, and there is no centralized exchange. A seller has to contact multiple potential buyers and the comparison of used aircrafts is costly and time-consuming. In addition, a sale involves legal costs, especially when there are legal disputes over the title.

[17] The welfare impact is nuanced, however: the erosion in asset market experience could reduce lenders' ability to efficiently liquidate firm assets.

increase in the secondary asset market turnover in (23)) and hence a depreciation of lenders' experience (i.e., a decrease of π in (22)). Our model would thus predict an enhanced incentive for lenders to monitor borrowers following these transformations.

ii) *Legal and Bankruptcy Reforms.* A second scenario in which our analysis can yield new insights consists of the impact of legal and bankruptcy reforms on credit market behavior. Previous studies have highlighted the possible impact of such reforms on the ability of individual lenders to extract value from asset liquidation. In particular, some analyses (e.g. Cerqueiro et al., 2016) have employed legal shocks that directly affect the recovery rate of collateral assets during liquidation (that is, a shock to λ in our theoretical framework). Our model shows that the ultimate impact of such shocks depends not only on λ but also on banks' experience stemming from capital allocation engagement (π). While legal shocks are useful to identify banks' average reactions, they forego the heterogeneity that stems from banks' experience.[18]

For instance, a change in bankruptcy procedures can make it easier for creditors to repossess and liquidate capital assets, a direct effect such as that captured by Cerqueiro et al. (2016). This can be visualized as the direct effect of an increase in λ in (22) (for given $p_{lead}(.)$), which tends to raise the value that lenders obtain from asset liquidation. On the other hand, by affecting the use of secondary asset markets by creditors, such a bankruptcy law reform can also reduce the relevance of bank experience in the secondary asset market by depreciating past experience (because of increased asset turnover in the secondary market). This can be visualized as the indirect effect of an increase in λ in (22) (through $p_{lead}(.)$), which reduces the asset liquidation value. Thus, our analysis can help disentangle the contrasting effects of a legal/bankruptcy reform, which could instead be neglected if one focused only on the direct impact. In Appendix A.10, we further carry out a numerical simulation of the model that disentangles these opposite effects of a bankruptcy law reform on banks' incentive to monitor and on the structure of lending contracts.[19]

Recent history provides various examples of bankruptcy law reforms that could have affected the use of secondary asset markets, such as the major bankruptcy reforms of France

[18] Bank experience π itself may depend on the quality of bankruptcy and liquidation λ.

[19] For this simulation, we use the parameter values already considered for the analysis of section 2.5.4.

(2005), Germany (2012), Spain (2009), Italy (2012), and Hong Kong (2016). These reforms introduced a temporary stay of proceedings against creditors after the filing of bankruptcy. This effectively reduced the ability of creditors to repossess and resell collateral assets in secondary markets.

iii) *Credit Market Liberalizations.* Deregulations of credit markets can also affect the degree of turnover in secondary markets. Herrera, Minetti and Schaffer (2025) and Howes (2022), for example, show that the major US banking deregulation of the 1980s and early 1990s impacted the ease of reallocation of capital assets. Credit market liberalizations can then influence the intensity of capital reallocation in secondary markets, possibly affecting the experience accumulated by banks in the secondary asset market (such as depreciating their experience, i.e., reducing π in (22)). This points to an alternative channel of influence of credit market liberalizations, which could act as a stimulus to lenders' monitoring incentives.

3.2 Empirical Methodology

Based on our testable hypotheses outlined in section 2, we estimate two main empirical models. First, we examine how experience, especially capital allocation engagement, influences a bank's decision to act as a lead arranger (extensive margin). To do so, we employ a linear probability model specified as follows:

$$Prob(lead_{b,f,s,t}) = \alpha^{'} + \gamma * Capital\ allocation\ engagement_{b,s,t} + \\ + \beta_1 * B_{b,t} + \beta_2 * L_{l,t} + \beta_3 * F_{f,t-1} + \epsilon_{b,f,s,t}, \quad (24)$$

where *Lead* equals one when bank b is defined as a '*lead arranger*' of a loan to firm f in sector s at time t, and zero otherwise (Bharath et al., 2011).[20] The sample set for equation (24) includes all banks that have been active at least once as a lead arranger in our sample within the five years prior to the loan's issuance. The timing of the variables aligns with the idea that a firm with certain characteristics at time $t-1$ will seek a loan at time t. The main independent variable is *capital allocation engagement*, with its coefficient

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

(γ) measuring changes in the propensity to act as a lead arranger. $\alpha^{'}$ denotes different levels of time-invariant and time-varying fixed effects (further details below). L, F and B are several loan, firm and bank control variables (including proxies for bank co-lending experience and for relationship lending) that are discussed in detail in section 4.3, while ϵ is a loan-level idiosyncratic disturbance.

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

$$\begin{aligned} \textit{Lead lender share}(\%)_{b,f,s,t} = \alpha^{'} + \gamma * \textit{Capital allocation engagement}_{b,s,t} + \\ + \beta_1 * B_{b,t} + \beta_2 * L_{l,t} + \beta_3 * F_{f,t-1} + \epsilon_{b,f,s,t}, \quad (25) \end{aligned}$$

where *Lead lender share*(%) represents the share 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 γ 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 enables us to overcome this issue by including several detailed fixed effects. In the specified empirical models, we incorporate firm fixed effects to control for time-invariant omitted variables at the firm level. Additionally, we add bank-year and industry-year-firm rating category fixed effects to effectively isolate variations in credit supply and demand within the same industry, capturing simultaneous changes that might otherwise confound our estimates (Jiménez, Ongena, Peydró and Saurina, 2014; Giannetti and Saidi, 2019).[21] These fixed effects account for firm risk fundamentals (e.g., future prospects, analyst forecasts, profitability) and time-varying unobservable bank fundamentals (such as profitability, management policies, monetary conditions, and other balance sheet characteristics). Given the extensive time span of our data set, we effectively compare the same bank lending to different firms within the same industry and year. In 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.

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

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 originated in the United States. We construct this data set using various data sources: Thomson Reuters LPCs DealScan database, the Call Reports of the Federal Reserve Board of Governors (FRB), Compustat, hand-collected data on enforcement actions by the three main U.S. banking supervisory authorities (FDIC, OCC and FED), and Rauch (1999) classification on product complexity.

We begin with a brief description of the syndicated corporate loan market, as several studies have extensively analyzed this market (for instance, Sufi, 2007; Chodorow-Reich, 2014; Delis, Kokas and Ongena, 2017, 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. 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 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 Chodorow-Reich (2014) 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 into 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 number of repeated interactions because we would artificially sum the same bank members over multiple loan facilities within a loan package. 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 specifically structured for institutional investors and are almost entirely sold off in the secondary market (Irani, Iyer, Meisenzahl and Peydro, 2021). Notably, excluded term loans B constitute less than 2% of the total loans in our initial sample.[22]

To obtain information for the financial statements of banks, we hand-match DealScan with Call Reports as there is no common identifier between these datasets. We perform the matching using a fuzzy merge algorithm based on names and locations, and we manually

[22] 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. Non-bank 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.

review all matching results. This process links the DealScan's lender ID with the commercial bank ID (RSSD9001), ensuring a unique linkage for each lender. Because Call Reports are available on a quarterly basis, we link the loan data set on a quarter level by matching the date of the loan deal to 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.

To control for outliers, we exclude observations in the one percent from the upper and lower tails of the distribution of the regression variables. 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. Table 1 formally defines all the variables used in the empirical analysis, and Table 2 shows summary statistics.

4.2 Measuring Experience

We construct two measures of experience, namely *capital allocation engagement* and *co-lending*, using variation at the bank-sector and bank-bank levels, respectively. Further, we borrow measures of bank-firm experience (relationship lending) from previous literature.

Capital Allocation Engagement. As highlighted by our theoretical model, banks accumulate experience on the best second-hand users of collateral assets and the most suitable liquidation strategies by engaging in repeated transactions in secondary asset markets (Habib and Johnsen, 1999). Sheard (1994), Edwards and Fischer (1994) and Cecco and Ferri (1996) document that in Japan, Germany and Italy during restructurings banks acquire information and experience on capital asset disposal. In the 2010 EU-EFIGE survey on European firms and in the 2006 Capitalia survey on Italian firms, 55% of the firms declared that banks acquire expertise on firms' capital and its market. Loan officer surveys confirm these findings (Gustafson, Ivanov and Meisenzahl, 2021).

Building on our theoretical model of section 2, we construct a *capital allocation engagement* index as a measure of a bank's sectorial experience with firms that actively manage (retrade) their assets within a specific industry. It measures the asset turnover (sales of property, plant and equipment, acquisitions and capital expenditures) for each firm a bank is lending to in a particular sector (weighted by its loan exposure to firms in that sector) relative to the overall weighted asset turnover in that sector. Precisely, as noted, *capital allocation engagement* is defined as follows:

$$Capital\ allocation\ engagement_{b,s,t} = \frac{\sum_{f=1}^{F}(Asset\ transactions_{f,s,t} * Loan_{b,f,s,t})}{\sum_{b=1}^{B}\left(\sum_{f=1}^{F}(Asset\ transactions_{f,s,t} * Loan_{b,f,s,t})\right)}, \tag{26}$$

where $Asset\ transactions_{f,s,t}$ is the total of sales of property, plant, and equipment (SPPE), acquisitions (AQC), and capital expenditures (CAPX) for each firm f in sector s at time t (Cui et al., 2024); $Loan_{b,f,s,t}$ denotes the credit (in millions of dollars) granted by bank b to firm f in sector s at time t; and F and B capture the total number of firms and banks, respectively.[23] The capital allocation engagement index in (26) is constructed using Compustat data following Cui et al. (2024). Compustat provides information on the ownership changes of productive assets starting in 1971. We use the sales of property, plant and equipment (SPPE, data item 107 with combined data code entries excluded), acquisitions (AQC, data item 129 with combined data code entries excluded), and capital expenditures (CAPX, data item 128).

We inspected the values of the total capital reallocation turnover (the denominator of (26)). There is substantial dispersion across sectors in terms of the intensity of capital reallocation: the interquartile range variation is about \$4 billion. This is also true when we normalize total capital reallocation by a proxy for the size of the sector (the total value of

[23] Our sample's average and median loan maturity is approximately four years. Consequently, our proxy for capital allocation engagement reflects experience accumulated over several years of managing loans. In robustness checks, we adjust capital allocation engagement 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 adjustments confirm that our results are robust to variations in the measurement period of capital allocation engagement.

sales in the sector). Industries such as industrial machinery, chemicals, and transportation equipment exhibit a high intensity of capital reallocation (relative to total sales). On the other side of the industry spectrum, sectors such as tobacco products and leather products have a relatively low intensity of capital reallocation.

Other Forms of Bank Experience. $Co-lending_{b,j,t}$ experience 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, accounting for the reduced trustworthiness or increased perceived risk associated with sanctioned banks. The calculation begins with each bank's sanction status represented by a dummy variable D, where D equals one if the bank received a sanction and zero otherwise. We adopt a weighting scheme where $W = 0.5$ for sanctioned banks and $W = 1$ for those without sanctions. The *co-lending* experience between two banks, b and j, at time t is then calculated as follows:

$$Co-lending_{b,j,t} = \frac{1}{\mathcal{P}\{B_{b,j,t}\}} \sum_{B_{b,j,t}} \min(W_b, W_j) \times (\# \; of \; Loans)_{b,j,t}, b \neq j \;, \tag{27}$$

where $\mathcal{P}\{B_{b,j,t}\}$ denotes the total number of bank pairs formed in each syndicate, W_b and W_j are the weights assigned based on the sanction status of banks b and j, respectively, and $(\# \; of \; Loans)_{b,j,t}$ represents the number of loans co-shared between the banks during the period up to time t. To create this 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-year rolling window without taking into account the roles that the two lenders took in previous loans. This measure assigns a greater, weighted by sanction, 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 adjusting for the potential reduction in trustworthiness (or increase in perceived risk) associated with sanctions.

To capture enforcement actions, we follow Delis, Staikouras and Tsoumas (2016) and use their data set from 1999 to 2010. The authors screen the websites of the primary federal supervisors of 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 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.

Following Bharath, Dahiya, Saunders and Srinivasan (2011), we also construct a *relationship lending* variable as the number of previous interactions between a bank and a firm 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 compute the number of the lender-borrower pair's lending relations.

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 spread, maturity, loan type, and collateral. We include the *all-in-spread-drawn* (AISD) defined as the spread over LIBOR plus the facility fee (Ivashina, 2009), the natural logarithm of loan *maturity* in months, 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 use the natural logarithm of the market-to-book ratio (*tobin's q*) to proxy for the cost of equity, and the ratio of net income to total assets (*ROA*) to measure profitability, following Adams and Ferreira (2009). *Firm size* is measured by the natural logarithm of total assets. Regarding bank-level control variables, we consider the ratio of non-performing loans to equity as an indicator of credit risk and the natural logarithm of total assets to proxy for bank size (Delis, Kokas and Ongena, 2017). In the baseline

[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).

specifications, bank-time fixed effects absorb these bank-level control variables.

5 Main Results

In this section, we test the main implications of the model outlined in section 2.

5.1 Baseline Estimates

Table 3 presents the results illustrating how banks' past experience affects the extensive margin of syndicated loans. In column I, we regress an indicator for being the lead lender on *capital allocation engagement*, while using a broad range of controls and detailed fixed effects. In columns II and III, we include all bank experience variables and various levels of fixed effects. We find a positive impact of *capital allocation engagement* (and other forms of bank experience, consistent with Hypothesis 2) on the probability that a bank is selected as the lead arranger. These results hold across various specifications, even when the regression model is saturated with supply, demand, and bank-industry matching fixed effects, as noted at the bottom of the table. Economically, the estimates from column III suggest that a one-standard-deviation increase in *capital allocation engagement* raises the probability of being a lead arranger by approximately 3 percentage points.

In Table 4, we turn to study hypothesis 1, that is, the impact of different forms of prior experience on the loan 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 lead lender share, we obtain strikingly different results across types of experience. While co-lending experience and relationship lending shrink the loan share the lead arranger retains, *capital allocation engagement* increases the loan share of the lead arranger (consistent with Hypothesis 1), after controlling for firm time-invariant characteristics (firm FE), credit supply (bank*year FE), industry demand (industry (SIC3)*year*rating FE), and unobserved components of the time-invariant matching between banks and certain industries (bank*SIC3 FE). Economically, its impact is significant: for example, in column III of Table 4, a one-standard-deviation increase in *capital allocation engagement* raises the lead share by almost 3.5 percentage points. Conversely, a one-standard-deviation increase in *co-lending* decreases the lead share by 1.8 percentage points.

Recall that the lead share is viewed as a proxy for the degree of moral hazard within a lending syndicate (Sufi, 2007; Ivashina, 2009). Thus, the estimates suggest that moral hazard within syndicates may be more severe when the lead arranger has stronger experience about capital (re)allocation in the sector. This is consistent with the results of the theoretical model of loan syndication in section 2. In the model, a larger experience about capital (re)allocation in the sector 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 monitoring incentives, participant lenders request the lead arranger to retain a larger loan share (part i of Testable Hypothesis 1). This result on the effects of sector experience contrasts with the findings for lead lenders' experience on co-lenders (co-lending experience) and on the borrower (relationship lending), which instead tend to reduce the lead arranger share. The theoretical model of section 2 (part ii of Testable Hypothesis 1) predicted such effect, rationalizing it with the reduced monitoring cost that is faced by a lead arranger with larger experience about co-lenders and about the borrower.

In Appendix Table B.1, we replicate the analysis of columns II and III of Table 4, this time focusing on the specific effects of each component of capital allocation engagement — acquisitions (AQC), capital expenditures (CAPX), and sales of property, plant, and equipment (SPPE) — on the loan share held by lead lenders. This detailed breakdown provides insight into how different asset engagement activities influence lead lenders' share retention. All components of capital allocation engagement positively affect lead lenders' share retention, with capital expenditures (CAPX) exhibiting the most substantial impact.

While our primary focus in Tables 3 and 4 is on the coefficient estimates for the bank experience variables, it is reassuring that the estimated coefficients on the control variables tend to have the expected signs. For instance, the spread negatively impacts the shares held by the lead lender, echoing the findings of Ivashina (2009). Furthermore, loan deals

[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.

with longer maturity tend to be riskier and, hence, banks can be less inclined to act as lead arrangers and also retain lower shares. In 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.

6 Mechanisms

The results of the previous tables show 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 variation in various dimensions in order to test hypotheses 3 and 4 of the theoretical model. The goal is to verify that the estimated effects of our proxies for different types of bank experience are indeed driven by prior knowledge and information accumulated by lenders in lending syndicates. In particular, we assess whether our proxy for capital allocation engagement has 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) and scenarios in which banks' lending is more asset-based (Testable Hypothesis 4). Such tests can further validate our identification strategy and mitigate concerns about omitted variables. Additionally, in the last part of this section, we investigate whether banks' capital allocation engagement affects their use of covenants in loan contracts, a proxy for contractual restrictions and monitoring mechanisms.

Sector Complexity and Information Sensitivity. In Table 5, we exploit data on the informational complexity of the products in the sectors to better disentangle the role of the bank-industry *capital allocation engagement*. 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).[26] 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 industries 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' engagement with asset (re)allocation 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' capital allocation engagement is stronger for industries with high informational complexity. For example, column I of Table 5 reveals that higher bank experience on capital (re)allocation in industries with heterogeneous products increases the lead lender loan share compared to non-complex industries (column II of Table 5).

Asset-based Lending. The theoretical model predicts that capital allocation engagement should 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). To capture the relevance of asset-based lending, we measure the capital intensity of firms by industry.[27] *Capital intensity* is a dummy variable equal to one when an industry's value of physical capital per worker is above the sample mean, and zero otherwise. This likely captures technological features of the sectors in which firms operate and, hence, may suffer less from endogeneity issues than firm-level measures. In Table 6, we interact our measure of capital allocation engagement with sectorial capital intensity. The results consistently show that the effect of *capital allocation engagement* is larger when capital intensity is higher.

Capital Allocation Engagement and Use of Covenants. Restrictive covenants in loan contracts are aimed at reducing the risk that borrowers engage in actions that reduce

[26] 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.

[27] Professionals have long differentiated between cash-flow lending (CFL) and asset-based lending (ABL), and scholars increasingly underscore their differences as well (Calomiris et al., 2017; Kim and Kung, 2017; Kermani and Ma, 2020, 2023). Previous studies emphasize two aspects of ABL. First, its underwriting process revolves primarily around collateral liquidation values. Second, the monitoring activity in ABL mainly focuses on the collateral itself, with a particular emphasis on accounts receivable and inventory.

their ability to repay loans (see, e.g., Giometti, Güler and Pietrosanti, 2024, on the link between specialized lenders and the use of covenants as a monitoring device). To the extent that capital allocation engagement raises the ability of lenders to extract value from firms' assets, we could then expect that lenders are less inclined to demand stringent covenants.

In Panel A of Table 7, we display the correlations between our measure of capital allocation engagement and various measures of use of covenants: the total number of restrictive covenants included in loan contracts, defined as the sum of general and financial covenants; the number of general covenants (contractual restrictions imposed on borrowers, including non-financial covenants); and the number of financial covenants (loan contract provisions requiring the borrower to maintain certain financial ratios). The pairwise correlations reveal a negative relationship, suggesting that banks more experienced in asset liquidation (with higher capital allocation engagement) impose fewer covenants in loan contracts. This supports the hypothesis of substitutability between collateral asset expertise and monitoring, where banks with greater experience in the secondary asset market rely less on contractual restrictions. Put differently, lenders specializing in asset liquidation reduce broad contractual restrictions and resort less to contractual monitoring mechanisms, such as limitations on asset sales or dividend payouts, as they rely more on their ability to recover value from assets in the event of default, and expect higher recoverability in case of asset liquidation.

The regression estimates in Panel B of Table 7 confirm the conclusion that banks with greater experience about capital asset (re)allocation impose fewer covenants. Rather than relying on ex-ante monitoring through restrictive covenants, these banks place more emphasis on ex-post asset recovery and resale. Overall, this suggests that capital allocation engagement captures a distinct lending model, where banks adjust loan contract design based on their confidence in recovering value upon default. At the same time, the negative but insignificant regression coefficient on *Financial covenants* suggests that while banks reduce general restrictions, they still maintain some financial oversight: financial covenants (e.g., leverage or interest coverage ratios) serve as early warning indicators of borrower distress. Even if a bank has experience on asset liquidation, it may still want to prevent borrower financial deterioration to avoid unnecessary liquidation costs.

Is It Bank Portfolio Riskiness? A potential concern about our results is that banks with high capital allocation engagement may simply be lending to riskier firms, which could explain the lower use of covenants. As a measure of a firm's financial stability, we consider a firm's Z-score, where higher values indicate lower risk of default. In Panel B of Table 7, the lack of a significant relationship between capital allocation engagement and the borrowing firm's Z-score suggests otherwise. If high-engagement banks were simply taking on riskier borrowers, we would expect to see a negative relationship with the Z-score (indicating that they lend to weaker firms). The results show instead that these banks are not necessarily lending to riskier firms but rather adjusting their contracts based on their ability to recover asset value in case of default. This points to an important conclusion: capital allocation engagement captures a bank's liquidation expertise, not its willingness to take on risk.

7 Further Tests and Robustness

Bank Specialization. In Appendix Table B.2, we expand our sensitivity analysis and experiment with an alternative indicator to capture lenders' information advantage in extending loans. This indicator is based on the works of Blickle et al. (2023) and Paravisini et al. (2023), which measure the bank's specialization in lending. We calculate the $specialization_{b,s,t}$ as the total credit ($M) from bank b to firms in a two-digit SIC sector s at time t over the total outstanding lending ($M) by bank b to all sectors:

$$Specialization_{b,s,t} = \frac{\sum_{f=1}^{F} Loan_{b,f,s,t}}{\sum_{s=1}^{S}\sum_{f=1}^{F} Loan_{b,f,s,t}}\ , \tag{28}$$

where $Loan_{b,f,s,t}$ is the credit granted by bank b to firm f in sector s at time t. F and S denote the total number of firms and sectors, respectively. This index ranges from zero to one, with higher values reflecting higher specialization in the firm's sector.

We re-estimate our baseline specifications by adding the *specialization* variable. The estimated coefficient on *capital allocation engagement* remains essentially unchanged compared to the baseline results. Interestingly, the coefficient of *specialization* is positive and statistically significant, consistent with Blickle et al. (2023) and Paravisini et al. (2023).

While *capital allocation engagement* and *specialization* exhibit the same sign and significance, they capture different dimensions of lending behavior. Specifically, our measure of *capital allocation engagement* reflects the importance of a bank's lending experience in industries with similar assets, whereas *specialization* highlights how crucial a specific sector is within a bank's overall portfolio.

Non-linearities. The theoretical considerations discussed in section 2 can suggest a non-linear relationship in banks' learning by experience. Appendix Table B.3 investigates this by including squared terms of the experience variables. Our results suggest a possible inverted U-shaped relationship for capital allocation engagement and lead lender shares, and a U-shaped relationship for co-lending experience. Specifically, the turning point for capital allocation engagement occurs at a value of 0.85 (the 95th percentile of its distribution). On the other hand, the turning point for the number of previous co-lending relationships is 30 interactions, reflecting a high number of past interactions between banks.

Alternative Specifications. In Appendix Table B.4, we further subject our findings to a variety of robustness tests. In columns I-II, 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 III-IV, we exclude loans originated for leveraged buyouts (LBOs) or mergers and acquisitions (M&As) because these loans can reduce the asymmetric information between the bank and the borrowing firm due to the purpose of the loan (Ivashina and Kovner, 2011). Finally, in columns V-VI, 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. These results are almost identical to the baseline results, pointing to the robustness and consistency of our findings.

8 Conclusions

Experience is traditionally viewed as a fundamental mechanism of acquisition of information and knowledge in the banking sector. In this paper, we model and empirically document the impact of a novel channel of banks' credit market experience: capital allocation engagement. This captures a bank's experience about the reallocation of physical capital in the sector in which the borrowing firm is active. Banks with greater capital allocation engagement learn more about secondary market trading in the sector. We study this capital allocation engagement next to other forms of credit market experience such as firm experience through relationship lending, co-lending experience and industry specialization.

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 experience about capital (re)allocation exacerbates moral-hazard issues. Exploiting cross-section heterogeneity across firms and banks, we further find that the dilution of banks' monitoring incentives induced by experience about the process of capital (re)allocation is particularly pronounced for industries and products with high information complexity.

The analysis leaves open relevant questions. 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). In the context of banks' experience about capital (re)allocation, we expect both codified experience at the level of the banking institution and soft experience at the level of loan officers to play a role. Teasing out the relative importance of the two sources of experience could help further understand the implications for loan arrangements and lending outcomes. We leave these and other relevant issues to future research.

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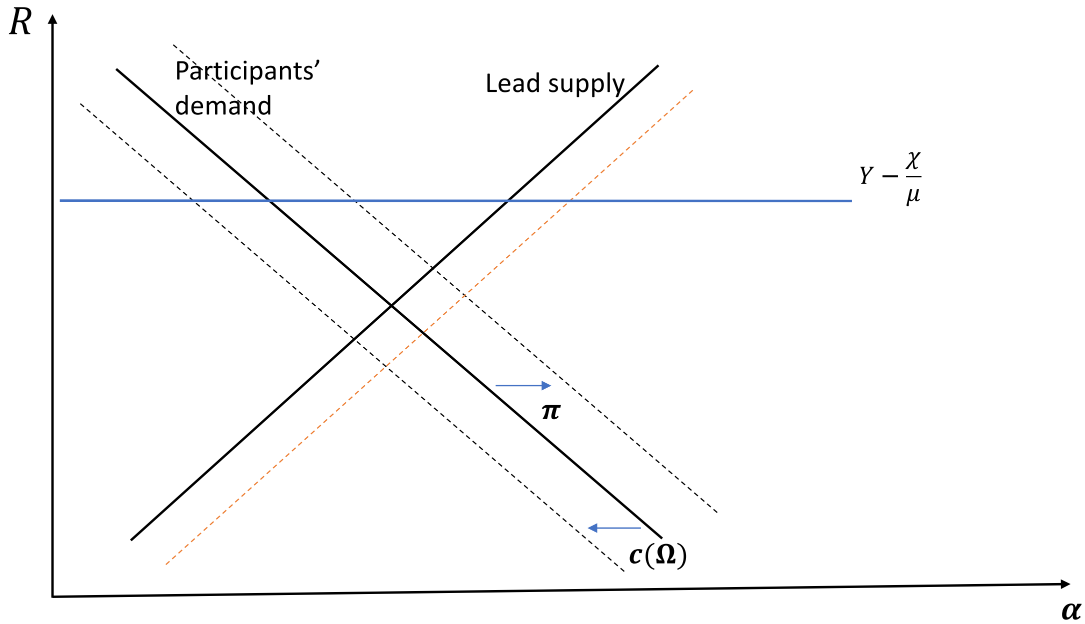
Figure 1: Lead share demand and supply curves



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.

Table 1: Variable definitions and sources

Name	Description	Source
Dependent variables:		
Lead bank	Dummy variable equal to one if the bank 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:		
Capital allocation engagement	We define the capital allocation engagement share by integrating the firm's active participation in the asset market within a two-digit SIC sector (SIC2), as reflected through sales of Property, Plant, and Equipment (SPPE), acquisitions (AQC), and capital expenditures (CAPX). This measure is weighted by the lead lender's share. Specifically, it quantifies the engagement of a bank within a SIC2 sector by calculating the weighted sum of a firm's asset market activities, factoring in the bank's share, relative to the total market activities supported by all banks in the sector: $Capital\ allocation\ engagement_{b,s,t} = \frac{\sum_{f=1}^{F}(Asset\ transactions_{f,s,t} * Loan_{b,f,s,t})}{\sum_{b=1}^{B}\left(\sum_{f=1}^{F}(Asset\ transactions_{f,s,t} * Loan_{b,f,s,t})\right)}$. Capital allocation engagement lies between zero and one, with higher values indicating a higher lending concentration to sectors with higher intensity of participation in the asset market.	Own calculations
Loan-level explanatory variables:		
Co-lending	The number of loans the lead arranger syndicates with participant lenders in the last five years prior to a current loan weighted for enforcement actions. Bank co-lending, can be calculated as follows: $Co-lending_{b,f,t} = \frac{1}{\mathcal{P}\{B_{b,j,t}\}} \sum_{B_{b,j,t}} \min(W_b, W_j) \times (Number\ of\ Loans)_{b,j,t}$ where: $\mathcal{P}\{B_{b,j,t}\}$ denotes the total number of bank pairs formed in each syndicate, W_b and W_j are the weights assigned based on the sanction status of banks b and j, respectively, and $(Number\ of\ Loans)_{b,j,t}$ represents the number of loans co-shared between banks b and j during the period leading up to time t.	Own calculations
Relationship lending	The number of loans a bank lends to the same borrower in the last five years prior to a current loan.	Own calculations
Spread	All-in-spread-drawn spread is defined as the sum of the spread over LIBOR plus the facility fee (bps).	DealScan
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
Firm rating category	Indicator variable for investment grade, non-investment grade and unrated firms.	Compustat
Bank-level explanatory variables:		
Bank specialization	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): $$Sector - Experience_{b,s,t} = \frac{\sum_{f=1}^{F} Loan_{b,f,s,t}}{\sum_{s=1}^{S}\sum_{f=1}^{F} Loan_{b,f,s,t}}.$$ This index ranges from zero to one, with higher values reflecting higher exposure in the sector in which the firm operates.	Own calculations
NPLs	Nonperforming loans divided by bank's equity.	Call reports
Bank size	The natural logarithm of the bank's total assets.	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.	Guiso and Minetti (2010)

Table 2: Summary statistics

Variables	Level	Obs	Mean	STD	Min.	Median	Max
Panel A: Summary statistics							
Lead lender	Bank	61,858	0.24	0.43	0.00	0.00	1.00
Lender shares (%)	Bank	61,858	19.66	25.95	0.00	10.00	100.00
Capital allocation engagement	Bank	61,858	0.05	0.08	0.00	0.02	1.00
Capital allocation engagement (AQC)	Bank	60,115	0.05	0.09	0.00	0.02	1.00
Capital allocation engagement (CAPX)	Bank	61,858	0.05	0.08	0.00	0.02	1.00
Capital allocation engagement (SPPE)	Bank	61,291	0.05	0.10	0.00	0.01	1.00
Co-lending	Bank	61,858	0.59	3.22	0.00	0.00	72.00
Bank specialization	Bank	61,858	0.08	0.15	0.00	0.03	1.00
Relationship lending	Loan	61,858	0.24	0.98	0.00	0.00	35.00
Spread	Loan	61,858	132.24	111.84	0.00	100	1,400
Maturity	Loan	61,858	3.59	0.74	-2.71	3.87	5.89
Collateral	Loan	61,858	0.38	0.48	0.00	0.00	1.00
Term	Loan	61,858	0.07	0.26	0.00	0.00	1.00
General covenants intensity	Loan	61,858	2.42	2.60	0.00	2.00	9.00
Performance precing	Loan	61,858	0.51	0.50	0.00	1.00	1.00
Tobin's q	Firm	61,858	1.74	2.37	0.34	1.42	203.47
ROA	Firm	61,858	0.02	0.31	0.00	0.01	31.34
Firm size	Firm	61,858	7.24	1.83	-1.97	7.23	14.57
Product complexity	Firm	11,563	0.74	0.44	0.00	1.00	1.00
Capital intensity	Firm	61,858	0.57	0.50	0.00	1.00	1.00
NPLs	Bank	61,858	0.06	0.27	0.00	0.00	39.75
Bank size	Bank	61,858	17.83	2.01	8.54	17.87	21.58
Asset-based lending	Bank	61,858	0.11	0.31	0.00	0.00	1.00
Panel B: Variation for the main variable of interest							
		Between	Within				
Capital allocation engagement	Bank	0.02	0.08				

The table provides descriptive statistics. Panel A reports summary statistics for the main variables used in analysis. Panel B shows that the variation in the variable of interest is within banks. The variables are defined in table 1.

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

	I	II	III
Dependent variable:		*Prob(lead lender)*	
Capital allocation engagement	0.328***	0.321***	0.331***
	[10.370]	[10.362]	[11.074]
Co-lending		0.020***	0.017***
		[4.606]	[5.402]
Relationship lending		0.170***	0.137***
		[30.328]	[37.477]
Spread	-0.000	-0.000	-0.000
	[-0.424]	[-0.457]	[-0.072]
Maturity	-0.030***	-0.030***	-0.026***
	[-5.709]	[-5.644]	[-7.217]
Collateral	0.010	0.009	0.003
	[1.266]	[1.216]	[0.447]
Term	0.032***	0.035***	0.026***
	[3.565]	[3.789]	[3.486]
General covenants	-0.011***	-0.012***	-0.008***
	[-7.983]	[-7.867]	[-7.440]
Performance pricing	-0.023***	-0.024***	-0.018***
	[-3.623]	[-3.769]	[-3.835]
Tobin's q	0.000	0.000	-0.000
	[0.028]	[0.166]	[-0.038]
ROA	0.003	0.004	0.001
	[0.438]	[0.526]	[0.263]
Firm size	-0.068***	-0.067***	-0.060***
	[-8.549]	[-9.086]	[-9.931]
NPLs			0.004
			[0.188]
Bank size			0.021
			[1.370]
Observations	57,900	57,900	54,740
R-squared	0.565	0.581	0.618
Year FE			Y
Firm FE	Y	Y	Y
Bank*Year FE	Y	Y	
Industry (SIC3)*Year*Rating FE	Y	Y	
Bank*Industry (SIC3) FE			Y
Clustered standard errors	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. The sample consists of syndicated loan-level data 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
Dependent variable:	*Lead lender shares (%)*		
Capital allocation engagement	34.278***	33.708***	29.492***
	[6.399]	[6.280]	[5.829]
Co-lending		-0.552**	-0.437***
		[-2.481]	[-2.861]
Relationship lending		-0.475**	0.070
		[-2.521]	[0.318]
Spread	-7.849***	-7.878***	-6.851***
	[-8.674]	[-8.684]	[-10.449]
Maturity	2.370**	2.319**	2.440*
	[2.164]	[2.219]	[1.949]
Collateral	7.954***	7.904***	7.746***
	[6.554]	[6.501]	[11.720]
Term	-1.983***	-1.948***	-1.554***
	[-4.311]	[-4.330]	[-5.048]
General covenants	-6.369***	-6.219***	-6.263***
	[-4.233]	[-4.359]	[-5.482]
Performance pricing	0.025	0.034	-0.010
	[0.616]	[0.815]	[-0.162]
Tobin's q	-0.317	-0.198	-0.306
	[-0.567]	[-0.332]	[-0.943]
ROA	-7.235***	-7.059***	-6.635***
	[-6.907]	[-7.022]	[-8.704]
Firm size	-0.000	-0.000	-0.002
	[-0.073]	[-0.039]	[-0.602]
NPLs			-0.579
			[-0.491]
Bank size			-0.406
			[-0.255]
Observations	11,874	11,874	14,671
R-squared	0.858	0.861	0.791
Year FE			Y
Firm FE	Y	Y	Y
Bank*Year FE	Y	Y	
Industry (SIC3)*Year*Rating FE	Y	Y	
Bank*Industry (SIC3) FE			Y
Clustered standard errors	Bank	Bank	Bank

The table reports coefficients and t-statistics (in brackets) for lead lenders. The dependent variable is the lead lender shares (%). The sample consists of syndicated loan-level data 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: Experience and product information complexity

	I	II	III	IV
Dependent variable:	*Lead lender shares (%)*			
Group:	Complex	Non-complex	Complex	Non-complex
Capital allocation engagement	37.671**	34.071***	29.454***	26.888***
	[2.472]	[5.343]	[5.345]	[4.401]
Chow test (P-Value)	0.000	0.000	0.000	0.000
Loan controls	Y	Y	Y	Y
Firm controls	Y	Y	Y	Y
Bank controls		Y		Y
Observations	1,573	9,819	2,199	8,896
R-squared	0.905	0.860	0.814	0.791
Year FE			Y	Y
Firm FE	Y	Y	Y	Y
Bank*Year FE	Y	Y		
Industry (SIC3)*Year*Rating 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) for different sub-samples based on Rauch (1999) classification of product information complexity. The dependent variable is the lead lender shares (%). The sample consists of syndicated loan-level data originated from 1987 to 2014. We 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, firm and bank control variables: $Co-lending$, $Relationship\ lending$, $Spread$, $Maturity$, $Collateral$, $Term$, $General\ covenants$, $Performance\ pricing$, $Tobin's\ q$, ROA, $Firm\ size$, $NPLs$ and $Bank\ size$. 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 asset market conditions

	I	II
Dependent variable:	*Lead lender shares (%)*	
Capital allocation engagement	20.575***	23.897***
	[3.016]	[5.018]
Capital allocation engagement * Capital intensity	25.344***	10.215**
	[2.998]	[2.465]
Loan controls	Y	Y
Firm controls	Y	Y
Bank controls		Y
Observations	11,874	14,671
R-squared	0.861	0.791
Year FE		Y
Firm FE	Y	Y
Bank*Year FE	Y	
Industry (SIC3)*Year*Rating FE	Y	
Bank*Industry (SIC3) FE		Y
Clustered standard errors	Bank	Bank

The table reports coefficients and t-statistics (in brackets). The dependent variable is the lead lender shares (%). 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, firm and bank control variables: $Co-lending$, $Relationship\,lending$, $Spread$, $Maturity$, $Collateral$, $Term$, $General\ covenants$, $Performance\ pricing$, $Tobin's\ q$, ROA, $Firm\ size$, $NPLs$ and $Bank\ size$. 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, Covenants, and Portfolio Riskiness

Panel A: Correlation matrix

	(1)	(2)	(3)	(4)	(5)
(1) Capital allocation engagement	1.000				
(2) Total covenants	-0.137***	1.000			
(3) General covenants	-0.138***	0.969***	1.000		
(4) Financial covenants	-0.114***	0.896***	0.757***	1.000	
(5) Z-score	-0.002	0.004	0.002	0.005*	1.000

Panel B: Regression estimates

	I	II	III	IV
Dependent variable:	Total covenants	General covenants	Financial covenants	Z-score
Bank-industry asset engagement	-0.485***	-0.314**	-0.170	-0.024
	[-2.957]	[-2.251]	[-1.406]	[-0.343]
Bank co-lending	0.020***	0.013***	0.007***	0.002**
	[2.867]	[2.679]	[2.997]	[2.054]
Relationship lending	0.031	0.018	0.012	-0.013*
	[1.330]	[1.391]	[1.139]	[-1.802]
Loan controls	Y	Y	Y	Y
Firm controls	Y	Y	Y	Y
Bank controls	Y	Y	Y	Y
Observations	13,851	13,851	13,851	13,110
R-squared	0.800	0.790	0.756	0.888
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Bank*Industry(SIC3)*Rating FE	Y	Y	Y	Y
Clustered SE (Bank level)	Y	Y	Y	Y

The table reports coefficients and t-statistics (in brackets). The dependent variable is the number of covenants (total, general or financial) or the Z-score. 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, firm and bank control variables: *Spread*, *Maturity*, *Collateral*, *Term*, *General covenants*, *Performance pricing*, *Tobin's q*, *ROA*, *Firm size*, *NPLs* and *Bank 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.

Online Appendix

"Banking on Experience. Capital Reallocation, Asset Knowledge, and the Structure of Lending Contracts"

This Online Appendix contains the proofs of the model and details on model robustness and extensions (Appendix A) as well as 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 about capital (re)allocation, π, and increasing in the level of his experience Ω about the borrower and the co-lenders.

Define

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

G is decreasing in μ since

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

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

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

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

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

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

We can also show that

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

Therefore, by the implicit function theorem,

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

Similarly,

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

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,

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

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

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

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 about capital re)allocation rises, while it shifts inward when lead lenders' experience Ω about the borrower and the co-lenders increases.

Define

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

We have

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

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

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

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

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

which implies that

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

Further, we have

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

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,

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

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' experience π about capital (re)allocation rises. Moreover,

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

When $\eta = 0$, it reduces to

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

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

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

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

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

In turn,

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

We have that

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

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 about capital (re)allocation rises is

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

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.

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

When $\eta = 0$, it simplifies to

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

In this case,

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

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,

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

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

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

We also have

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

Therefore,

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

A.4 Information complexity and lenders' experience

Here we assume that the probability that a lead lender observes a more informative signal is $\psi\pi$, where ψ 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, $\frac{\partial^2\alpha}{\partial\pi\partial\psi} > 0$ 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 ψ.

A.5 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,

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

and

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

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

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

Similar to the main model,

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

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

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

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

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

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

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

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

and that

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

Optimal monitoring. The optimal μ is again solved from the first order condition $\alpha\,(R - p_{lead}\lambda A) - c(\Omega)\mu = 0$ 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

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

We can show that

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

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.6 Endogenous sectoral experience accumulation

We outline a model framework in which the acquisition of sectoral experience π is endogenized. The liquidation market operates as in the main model. We assume that acquiring sectoral experience incurs a quadratic cost of $\frac{c_\pi \pi^2}{2}$, and this decision is made simultaneously with the choice of monitoring effort. The optimization problem in equation (10) is thus modified to:

$$\max_{\mu,\pi} \left\{ \alpha\mu R + \alpha(1-\mu)p_{lead}\lambda A - \frac{c(\Omega)\mu^2}{2} - \frac{c_\pi \pi^2}{2} - \phi(\alpha) + \chi \right\}, \tag{29}$$

where $p_{lead} = \pi p_H + (1-\pi)p_L$, and each individual lender takes p_H and p_L as given. The first-order condition for μ remains the same as in equation (11), while the first-order condition for π is:

$$\alpha(1-\mu)(p_H - p_L)\lambda A - c_\pi \pi = 0. \tag{30}$$

Intuitively, the lead bank invests more in sectoral experience when it retains a larger lead share α, exerts less monitoring effort μ, holds more resalable assets λA, and when the price differential between the two liquidation markets $p_H - p_L$ is greater. The mechanisms of the model carry through in such a modified scenario. The main aspect worth noting is that, instead of reasoning in terms of variation in the degree of asset market experience π of a lender, one should reason in terms of variation in the cost c_π of acquiring such experience.

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

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

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

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

Similarly, the asset price in the low market is

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

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

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

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

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

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

$$\max_{\mu_i} \left\{ \alpha_i \mu_i R + \alpha_i (1-\mu_i) p_{lead} \lambda A_i - \frac{c(\Omega)\mu_i^2}{2} - \phi(\alpha_i) + \chi \right\}. \tag{31}$$

from which we obtain the first order condition

$$\alpha_i \left(R - p_{lead}\lambda A_i\right) - c(\Omega)\mu_i = 0. \tag{32}$$

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

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

where

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

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:

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

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 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

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

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

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

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

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

We obtain

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

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,

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

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

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

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

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

We obtain:

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

and

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

Since $\frac{\partial \mu}{\partial \pi} < 0$, $\frac{\partial F}{\partial \pi} < 0$ as long as β is not too small and therefore $(1-\mu)(1-\beta)(\overline{L} - \underline{L})\lambda A$ 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 experience π about capital (re)allocation shifts the demand curve to the right.

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

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

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

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

We have

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

and

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

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.9 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 [28]

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

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

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

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

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

from which

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

In comparison, in the decentralized equilibrium,

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

[28] Note that in deriving equation (21), we focus on a scenario with a degenerate distribution $F(Y)$ of firms' output over the relevant region.

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

$$\mu_p - \mu = \frac{\overbrace{-c\alpha[(V - p_{lead})\lambda A - (Y - R)]}^{W_1 \gtrless 0} + \overbrace{c(1-\alpha)(Y - V\lambda A)}^{W_2 > 0} + \overbrace{\frac{\partial V}{\partial \mu}\left[c - \alpha\left(R - p_{lead}\lambda A\right)\right]\lambda A}^{W_3 > 0}}{\underbrace{c\left(c + \frac{\partial V}{\partial \mu}\lambda A\right)}_{>0}}. \tag{33}$$

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.

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	1.11
Fraction of resalable assets	λ	0.90
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 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,

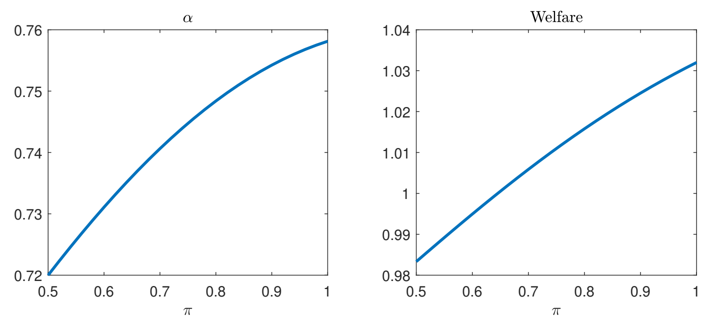


Figure A.1: The effect of sectorial experiences on decentralized equilibrium outcome.

more sectorial experience π increases the lead share in the equilibrium. It also raises the welfare of the economy.

A.10 Comparative statics of λ

We examine how the decentralized equilibrium outcome in the main model changes as λ, the fraction of resalable assets, varies. As noted in the main text (Section 3.1), an increase in λ can capture a change in bankruptcy laws that increases the ability of lenders to repossess and liquidate assets, following a bankruptcy reform. To investigate the effects of an increase in λ, we use the numerical example described above in Appendix A.9. Specifically, we vary λ from 0.8 to 1, holding all the other parameter values fixed as in Table A.1. The results are presented in Figure A.2.

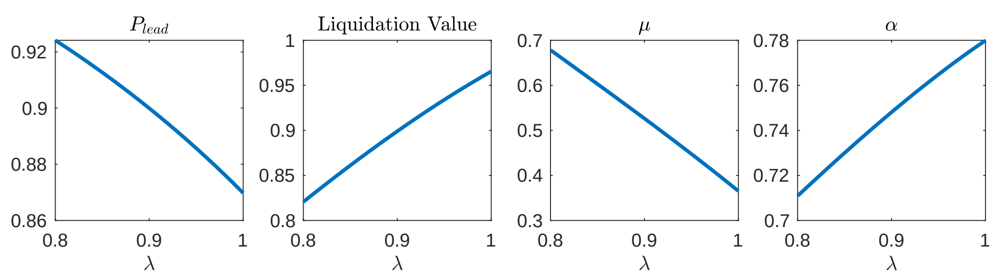


Figure A.2: The effect of λ on decentralized equilibrium outcome

As discussed in Section 3.1, the expected price received by a lead arranger, p_{lead}, decreases as a larger fraction of assets becomes resalable (i.e., as λ increases). This can effectively capture the depreciation in the asset market experience accumulated by a lead lender, due to the higher asset market turnover (indirect effect of λ). However, in our numerical example, the liquidation value of assets, given by $p_{lead}(\lambda, \pi)\lambda A$ in equation (22), still increases with λ, due the direct effect of λ. As expected, this results in a reduced monitoring effort by the lead lender (μ) and a higher lead share (α) demanded by participants.

Appendix B Additional Empirical Results

Table B.1: Lead lender shares (%) and components of capital allocation engagement

	I	II	III	IV	V	VI
Dependent variable:			*Lead lender shares (%)*			
Capital allocation engagement (AQC)	19.813***	7.484**				
	[8.126]	[2.151]				
Capital allocation engagement (CAPX)			46.234***	44.558***		
			[6.959]	[7.904]		
Capital allocation engagement (Sales PPE)					11.444***	17.854***
					[2.927]	[5.891]
Co-lending	-0.567**	-0.458***	-0.544**	-0.440***	-0.559**	-0.456***
	[-2.459]	[-2.909]	[-2.463]	[-2.920]	[-2.453]	[-2.974]
Relationship lending	-0.498***	0.021	-0.480**	0.064	-0.525***	0.023
	[-2.614]	[0.094]	[-2.543]	[0.278]	[-2.943]	[0.101]
Spread	-7.806***	-6.885***	-7.811***	-6.816***	-7.872***	-6.898***
	[-8.798]	[-10.444]	[-8.878]	[-10.107]	[-8.462]	[-10.218]
Maturity	2.516**	2.502*	2.253**	2.465*	2.234**	2.381*
	[2.390]	[1.936]	[2.131]	[1.920]	[2.130]	[1.920]
Collateral	7.834***	7.665***	7.806***	7.374***	8.049***	7.691***
	[6.147]	[9.968]	[6.294]	[11.384]	[6.600]	[11.552]
Term	-1.975***	-1.560***	-1.971***	-1.588***	-1.930***	-1.543***
	[-4.383]	[-4.892]	[-4.359]	[-5.186]	[-4.374]	[-4.956]
General covenants	-6.149***	-6.264***	-6.153***	-6.182***	-6.364***	-6.430***
	[-4.329]	[-5.609]	[-4.241]	[-5.423]	[-4.280]	[-5.421]
Performance pricing	0.016	-0.039	0.047	-0.007	0.035	-0.025
	[0.340]	[-0.582]	[1.172]	[-0.122]	[0.799]	[-0.376]
Tobin's q	-0.433	-0.361	-0.303	-0.230	-0.286	-0.314
	[-0.797]	[-1.193]	[-0.508]	[-0.652]	[-0.473]	[-0.965]
ROA	-6.876***	-6.278***	-6.969***	-6.550***	-6.952***	-6.429***
	[-6.712]	[-8.423]	[-6.929]	[-8.616]	[-7.012]	[-8.628]
Firm size	-0.001	-0.001	-0.000	-0.002	-0.000	-0.002
	[-0.245]	[-0.419]	[-0.070]	[-0.515]	[-0.067]	[-0.581]
NPL/Equity	-6.876***	-0.785	-6.969***	-1.241	-6.952***	-0.604
	[-6.712]	[-0.722]	[-6.929]	[-1.158]	[-7.012]	[-0.546]
Bank size	-0.001	-0.419	-0.000	-0.684	-0.000	-0.186
	[-0.245]	[-0.274]	[-0.070]	[-0.436]	[-0.067]	[-0.122]
Observations	11,658	14,291	11,895	14,716	11,814	14,497
R-squared	0.860	0.790	0.861	0.793	0.859	0.789
Year FE		Y		Y		Y
Firm FE	Y	Y	Y	Y	Y	Y
Bank*Year FE	Y		Y		Y	
Industry (SIC3)*Year*Rating FE	Y		Y		Y	
Bank*Industry (SIC3) FE		Y		Y		Y
Clustered standard errors	Bank	Bank	Bank	Bank	Bank	Bank

The table reports coefficients and t-statistics (in brackets) for lead lenders. The dependent variable is the lead lender shares (%). The sample consists of syndicated loan-level data 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 B.2: Experience and bank specialization

	I	II	III	IV
Dependent variable:	*Prob(lead)*		*Lead lender shares (%)*	
Capital allocation engagement	0.302***	0.327***	31.186***	28.862***
	[10.459]	[11.127]	[5.935]	[5.765]
Specialization	0.185***	0.080***	30.250***	18.656***
	[7.207]	[4.481]	[4.633]	[4.803]
Loan controls	Y	Y	Y	Y
Firm controls	Y	Y	Y	Y
Bank controls		Y		Y
Observations	57,900	54,740	11,874	14,671
R-squared	0.581	0.619	0.861	0.792
Year FE		Y		Y
Firm FE	Y	Y	Y	Y
Bank*Year FE	Y		Y	
Industry (SIC3)*Year*Rating 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). The dependent variable is the lead lender shares (%). 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, firm and bank control variables: $Co-lending$, $Relationship\ lending$, $Spread$, $Maturity$, $Collateral$, $Term$, $General\ covenants$, $Performance\ pricing$, $Tobin's\ q$, ROA, $Firm\ size$, $NPLs$ and $Bank\ size$. 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 nonlinearities

	I	II
Dependent variable:	*Lead lender shares (%)*	
Capital allocation engagement	57.213***	29.188***
	[4.976]	[3.008]
Capital allocation engagement^2	-48.941***	0.257
	[-2.719]	[0.015]
Loan controls	Y	Y
Firm controls	Y	Y
Bank controls		Y
Observations	11,874	14,671
R-squared	0.864	0.796
Year FE		Y
Firm FE	Y	Y
Bank*Year FE	Y	
Industry (SIC3)*Year*Rating FE	Y	
Bank*Industry (SIC3) FE		Y
Clustered standard errors	Bank	Bank

The table reports coefficients and t-statistics (in brackets). The dependent variable is the lead lender shares (%). 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, firm and bank control variables: $Co-lending$, $Relationship\ lending$, $Spread$, $Maturity$, $Collateral$, $Term$, $General\ covenants$, $Performance\ pricing$, $Tobin's\ q$, ROA, $Firm\ size$, $NPLs$ and $Bank\ size$. 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: Alternative specifications

	I	II	III	IV	V	VI
	Exclude NBER recessions		Exclude LBO		Exclude TOP3 banks	
Dependent variable:	*Prob(lead)*	*Lead lender shares (%)*	*Prob(lead)*	*Lead lender shares (%)*	*Prob(lead)*	*Lead lender shares (%)*
Capital allocation engagement	0.311***	35.401***	0.307***	34.776***	0.417***	60.676***
	[9.324]	[5.974]	[9.622]	[6.412]	[5.395]	[3.670]
Loan controls	Y	Y	Y	Y	Y	Y
Firm controls	Y	Y	Y	Y	Y	Y
Bank controls		Y		Y		Y
Observations	50,761	9,885	47,713	9,466	43,393	4,571
R-squared	0.582	0.864	0.596	0.881	0.649	0.919
Firm FE	Y	Y	Y	Y	Y	Y
Bank*Year FE	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

The table reports coefficients and t-statistics (in brackets). 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, firm and bank control variables: $Co-lending$, *Relationship lending*, *Spread*, $Maturity$, $Collateral$, $Term$, *General covenants*, $Performance\ pricing$, $Tobin's\ q$, ROA, $Firm\ size$, $NPLs$ and *Bank 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.