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JEL Classification: G21

Keywords: experience, relationship lending, M&A's, syndicated loans

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1 Introduction

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

In this paper, we study different dimensions of "learning by experience" in credit markets and their implications for lending. While some of the mechanisms through which lenders accumulate information are institutionalized (e.g., through information repositories such as credit bureaus and registers), the accumulation of credit market experience often occurs as a by-product of lending activities and day-to-day interactions. The syndicated loan market provides a natural setting for studying the impact of credit market experience on lending outcomes, firm behavior, and banks' (mis)behavior vis-à-vis other syndicate members. Over the course of frequent and repeated interactions in lending consortia, syndicate members learn from the actions and decisions of other syndicate members, and garner valuable experience on firms, sectors of activity and other banks. We can then unpack lenders' experience into its multiple dimensions and study to what extent its various components improve, or worsen, credit market outcomes.

To address our research question, we use syndicated loan-level data on 20,932 loans originated by 663 banks to 5,309 non-financial firms. The data span 64 industries (2 digit SIC) from 1987 until 2014. We match syndicated loans with detailed data on the characteristics of firms and banks as well as information on regulatory actions undertaken against

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

lead arrangers of the syndicated loans. Our data set allows us to construct three measures of experience accumulated by a bank. The first measure refers to $firm - experience$ and is based on the number of times that the bank has interacted with a firm in previous syndicates. A key feature of this measure is that it is constructed for all active banks and not solely for lead arrangers. This is important as a participant bank may also learn about a borrower during its interactions in a lending consortium. The second measure captures $sector - experience$, which relies on the sectoral specialization acquired by a bank through repeated interactions with borrowing firms operating in a specific sector. These two types of experience are often viewed as core components of relationship lending technologies (see e.g., Boot and Thakor, 2000). The third measure of experience focuses on interactions among banks and consists of the number of previous interactions between the lead arranger and participants in syndicated deals, i.e., $bank - experience$. This measure captures the degree of learning from prior interactions with other banks over the course of syndicated loans.

We first ask our data whether banks in loan syndicates actively learn about borrowers, industry and co-lenders over time (learning-by-participating). We find robust evidence of significant information spillovers in syndicated deals: the larger the number of prior interactions of a lender with a firm (i.e., $firm - experience$), the higher the likelihood that the lender will be a lead arranger in a future deal. Such a likelihood is also increasing in the two other forms of experience, $sector - experience$ and $bank - experience$.

We then turn to investigate to what extent prior experience is an attenuator or amplifier of moral hazard issues in syndicated loans. In the literature, the lead share is typically interpreted as a proxy for the degree of moral hazard in a syndicate: the larger the risk that the lead arranger shirks on its due diligence and monitoring effort, the larger is the share it should retain to raise its stake in the loan (Sufi, 2007). Our results suggest quite a nuanced impact of lenders' experience. While prior firm experience and bank experience of the lead arranger appear to reduce the need to concentrate the syndicated loan in the hands of the lead arranger, prior sectoral experience turns out to increase the lead share. Thus, the estimates suggest that moral hazard within syndicates can be more severe when the lead arranger has previously accumulated stronger sectoral experience. We surmise that this could be due to the lead arranger having a larger outside option in case of failure of the loan and that this may dilute its incentive to properly monitor the loan.[2] Overall,

[2]As we discuss in the theoretical background (Section 2), for a given level of lead bank's share in the loan, syndicate participants are less incentivized to participate in the deal due to the complementarity

while all forms of experience naturally ease banks' role as monitors (extensive margin), not necessarily they all reduce the risk that banks shirk on their monitoring tasks.

We perform a number of cross-sectional tests to confirm that the baseline results reflect banks' accumulation of knowledge and information through experience and to ascertain in what scenarios experience exerts a stronger influence. First, we exploit data on the informational complexity of products, similarly to Rauch (1999). In industries with higher shares of differentiated products, the effects of credit market experience can be more pronounced as there is larger uncertainty about product quality (Caballero, Candelaria and Hale, 2018). In line with expectations, we find that the effects of sectoral experience are more pronounced in industries characterized by higher informational complexity. Second, we exploit firm-level heterogeneity using sub-samples on firm profitability and informational opaqueness. The results suggest that the effects of lenders' experience are more pronounced for less profitable and more informationally opaque firms (Delis, Kokas and Ongena, 2017).

Third, we exploit heterogeneity in the composition of previous lending syndicates to ascertain the nature of bank-specific experience. We uncover evidence that bank-specific experience reflects not only common familiarity of the banks with the sector of activity of the borrowing firm, but also mutual trust built by the banks in their previous interactions. Finally, we exploit hand-collected information on regulatory enforcement actions enacted on banks that are active in the syndicated market. Sanctions impose a reputational stigma on punished banks (Delis, Iosifidi, Kokas, Xefteris and Ongena, 2020). We find that participants with prior $bank-experience$ with a punished lead arranger have a higher propensity to step up and start acting as a lead arranger. That is, experience enhances the flexibility with which banks can replace co-lenders hit by reputation shocks.

Overall, the results of the cross-sectional tests confirm the importance of banks experiences in the credit market. In addition, they allow disentangling the situations in which bank experience can affect heterogeneously their lending. The mechanism that underlies these findings is as follows. Bank's information acquisition via past transactions is crucial in screening and monitoring the accuracy of hard and soft information and thus reducing information asymmetries. As banks accumulate experience in sectors with higher information opacity, the effect of experience is more relevant.

Throughout the analysis, to control for unobserved factors and mitigate omitted-variable

between the lead lender's share and the outside option in case of borrower's default.

bias, we use the multi-level structure of our data set in a fashion similar to Jiménez, Ongena, Peydró and Saurina (2014, 2017). We acknowledge that it is challenging to control for all (observed and unobserved) firm and bank heterogeneity. However, our sample allows for the inclusion of year, bank, sector-year and bank-year fixed effects. These fixed effects saturate our analysis from other common shocks, time-varying supply side, and time-varying industry demand side effects.

In addition, we mitigate any lingering concern that banks' experience may be endogenous to the propensity to grant new loans or to the structure of loan syndicates by exploiting changes in credit market experience that stem from bank mergers (Favara and Giannetti, 2017). To this end, we use hand-collected information on bank mergers where both banks are active in the syndicated loan market in the year before the merger. Specifically, we instrument a bank's firm-sectoral-bank experience with information from the acquired bank in the last quarter of the pre-merger. This instrument is likely to satisfy the exclusion and relevance restrictions because it affects only peers' activities. Our results are fully robust to this IV strategy.

Related literature. To the best of our knowledge, this paper is the first that focuses exclusively on identifying the impact of the different dimensions of lenders' experience in the corporate lending market. Our study speaks to two 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). Also, there is substantial evidence that banks gather private information about their borrowers over multiple interactions (Boot, 2000; Ongena and Smith, 2000). Surprisingly, there is instead little evidence on how this information is used in future transactions not only with the same firm but also with other firms in the same industry and with co-lenders in loan syndicates. Our analysis can yield insights on how the value created by experience is shared between lenders and borrowers and among co-lenders.

Botsch and Vanasco (2019) pointed out the "learning by lending" practice as a potential substitute of banking relationships using syndicated loan data. By investigating the multiple dimensions of lenders' experience, and studying the role of $sector-$ and $bank-experience$, we find evidence that credit market experience can have ambiguous consequences for lending outcomes. It is then critical to capture the different angles of the accumulation of experience to sort out its ultimate impact on credit market outcomes. In contrast with Botsch and Vanasco (2019), we also analyse non-pricing characteristics that can be better linked with the value that additional information generates (Roberts and Sufi, 2009). Other works that have studied soft information in lending include, e.g., Agarwal and Hauswald (2010), Iyer, Khwaja, Luttmer and Shue (2016), Schwert (2018), Liberti and Petersen (2019) and Darmouni (2020). We contribute to these works by studying the different dimensions of experience in the credit market.

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

The remainder of the paper unfolds as follows. In Section 2, we lay out testable hypotheses on the effects of lenders' experience utilizing a parsimonious background model of syndicate loan participation. Section 3 describes the data and the empirical setting, while in Section 4 we provide details on the methodology. Section 5 presents the main results. Section 6 presents further tests that dissect the scenarios in which bank experience has stronger influence. Section 7 contains robustness tests and studies firm outcomes. Section 8 concludes.

2 Theoretical Background and Testable Predictions

In what follows, we frame testable hypotheses on the impact of banks' past experience on the extensive (decision to be the lead arranger of a syndicated loan) and intensive margin (share of loan retained by the lead arranger) of syndicated loans. 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 will see, 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 larger, or smaller, share of the loan to commit to monitoring the loan on behalf of the participants. The type of experience accumulated by the lender turns out to be critical for determining the sign of the effect.

Consider a syndicate that extends a loan with size normalized to one; the lenders can alternatively invest their funds at a market gross interest rate normalized to one. We call R the repayment on the loan. μ denotes the level of monitoring undertaken by the lead arranger, and is also the probability with which R is repaid by the borrower. With the complementary probability $1 - \mu$ the borrower defaults strategically and repays zero. The lead arranger faces a monitoring cost which is convex in the monitoring level, $\frac{c\mu^2}{2}$. Let α denote the share of the loan retained by the lead arranger and, correspondingly, $1 - \alpha$ the loan share of the participants. Hence, in case of success the repayment to the lead arranger is αR, and the repayment accruing to the syndicate participants is $(1 - \alpha)R$. Finally, we denote by Φ the outside option received by the lead arranger if the loan defaults. This can capture the salvage value of the collateral assets of the borrower, as determined, e.g., by the resale of assets to sectoral peers (Shleifer and Vishny, 1992; Habib and Johnsen, 1999).

Figure 1 is based on Ivashina (2009) and helps illustrate the setting. 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 gives the share under which a bank is willing to act as a lead arranger.

Intensive Margin. We investigate the two effects that the past experience accumulated by the lead arranger has on the retained share.

1) (*Substitutability between lead arranger's share and experience*) Past experience can make it cheaper for a lead arranger to monitor the borrower. We can represent this as 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 would expect the lead arranger to retain a lower share of the loan. In Figure 1, the participants' demand for the lead arranger's share is shifted downward.

More formally, the participation constraint of the syndicate participants reads

$$(1 - \alpha)R\widehat{\mu} = (1 - \alpha)$$

from which we obtain an inverse relation between the repayment requested by the participants and the induced monitoring of the lead arranger, $R = 1/\widehat{\mu}$. The gross benefit that the lead arranger derives from monitoring the borrower is given by $\alpha R\mu$. The monitoring μ^* chosen by the lead arranger will maximize her own expected net surplus S_L

$$\max\ S_L \equiv \left(\alpha R\mu - \frac{c\mu^2}{2} + (1-\mu)\Phi - \alpha\right)$$

from which $\mu^* = \frac{\alpha R - \Phi}{c}$. Therefore, for a given R, to induce a monitoring level $\widehat{\mu}$, α must be set at

$$\frac{\widehat{\mu}c + \Phi}{R} = \widehat{\alpha}.$$

If the past experience of the lead arranger Ω enters as an input that reduces the marginal cost of monitoring c, i.e. $c(\Omega)$, with $c'(.) < 0$, then

$$\frac{\widehat{\mu}c(\Omega) + \Phi}{R} = \widehat{\alpha}$$

and $\frac{\partial\widehat{\alpha}}{\partial\Omega} < 0$. Therefore, the implication is that an increase in past experience leads to a lower required minimum share α of the lead arranger. That is, we have a mechanism of substitutability between the lead arranger's share and her past experience (in Figure 1, the demand of participants shifts inward).

2) (*Complementarity between lead arranger's share and past experience*) A case of complementarity can arise if the past information of the lead arranger exacerbates the risk of her opportunistic behavior. Specifically, past experience can make the lead arranger "lazy", for example raising her outside option in case of borrower's default. Let the outside option of the lead arranger be now an increasing function of Ω itself, that is $\Phi(\Omega)$, with $\Phi'(.) > 0$. In this case, it will be necessary to concentrate the loan more in order to overcome the incentive of the lead arranger to shirk on her monitoring effort. Formally, the lead arranger will choose monitoring in order to

$$\max S_L \equiv \left(\alpha R\mu - \frac{c\mu^2}{2} + (1-\mu)\Phi(\Omega)\right) \Rightarrow \mu^* = \frac{\alpha R - \Phi(\Omega)}{c}.$$

So, to induce a monitoring $\widehat{\mu}$, α must be set at

$$\widehat{\alpha} = \frac{\widehat{\mu}c + \Phi(\Omega)}{R}$$

and $\frac{\partial\widehat{\alpha}}{\partial\Omega} > 0$. In Figure 1, the demand of participants shifts outward.

Let us now consider the participation constraint of the lead arranger. This allows us to plot the supply side curve in Figure 1, representing the repayment requested by the lead arranger for any lead share. The participation constraint reads:

$$\alpha R\mu + (1-\mu)\Phi - \frac{c\mu^2}{2} - \alpha = 0.$$

After replacing the monitoring choice of the lead arranger, and with the help of simple algebra, we obtain that the supply curve is upward sloping. Moreover, an increase in the outside option of the lead arranger $\Phi(\Omega)$ or a reduction in her monitoring cost $c(\Omega)$ reduce the repayment requested for any lead share, shifting the supply curve downward.

Hypothesis 1: The predicted impact of banks' experience on lead shares is ambiguous a priori. A lower lead share is more likely to be observed when banks' experience eases monitoring activities. By contrast, a higher lead share will be observed when experience boosts banks' outside option in the event of borrowers' default.

As noted, in the empirical analysis we study the effect of experience on borrower, banks, and sector of activity of the borrower. We expect all these types of experience to reduce the cost of acquiring new information (substitutability mechanism, $c'(.) < 0$). On the other hand, we expect the lender's outside option in case of borrower's default to be increasing in the lender's sectoral experience (complementarity mechanism, $\Phi'(.) > 0$). Shleifer and Vishny (1992) and Diamond and Rajan (2002), for example, show that the resale value of project loans in the event of borrower's default is increasing in the prior knowledge that the lender has accumulated on the redeployability of project loans among sectoral peers.

Extensive margin. Having studied the effects of experience on the concentration of syndicated deals, we can turn to study its effect on the likelihood that a syndicated loan is granted. Denoting by C_L the cost for a borrower of asking the loan and Y the borrower's return from using the loan, we have that a borrower will be willing to take a loan as long as

$$Y \geq R + C_L.$$

Let $F(Y)$ denote the probability that the borrower's return is less or equal to Y. As it can be grasped from Figure 1, it is immediate that

$$\frac{\partial[1 - F(R + C_L)]}{\partial c} \geq 0.$$

In Figure 1, both the demand and the supply curve are shifted downward when the cost of acquiring information is lower, reducing the repayment requested from the borrower ($\frac{\partial R}{\partial c}$ is strictly negative). On the other hand, the likelihood that a loan is established is ambiguously related to the outside option of the lead arranger $\Phi(\Omega)$. In Figure 1 the supply curve is shifted downward while the supply curve is shifted upward ($\frac{\partial R}{\partial c}$ is ambiguous ex ante).

Hypothesis 2: When banks' experience eases monitoring, the likelihood that the bank acts as a lead arranger will increase. If, instead, experience increases the bank's outside option, its predicted impact on the probability that the bank acts as a lead arranger is ambiguous.

3 Data and Measurement

3.1 Data Sources

We construct our data set drawing information from five 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 enacted 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 this market has been extensively analyzed by a number of studies (for instance, Dennis and Mullineaux, 2000; Sufi, 2007, among others). The main advantage of studying the syndicated market is that a group of banks co-finance a single borrower and banks' overlapping portfolios allow to measure different levels of past experience accumulated by syndicate members. In the past two decades syndicated lending has amounted to about half of total commercial and industrial (C&I) lending, and therefore it is often used to assess bank lending policies and the interactions between co-lenders and borrowers (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, covenant, a range for the interest rate, etc.). The members of the syndicate fall into three groups, namely 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 (paid by the borrower) for arranging and managing the syndicated loan.[3]

The information for the syndicated loans is based on the LPC DealScan. This data set provides transaction-level information on the loan deal's characteristics (amount, maturity, collateral, borrowing spread, performance pricing, etc.), as well as the banks of the syndicate, their roles, the share of each bank and the firm that receives the loan. We apply the following selection rules to avoid including bias in our sample and to provide a realistic insight on the structure of syndicates. First, we restrict our sample to a package-loan level instead of a facility-loan level. In our set-up, using a facility-loan level would create a selection bias on the numbers of repeated interactions because we would artificially sum the same bank members over multiple loan facilities within a loan package.[4] Second, we drop packages that are granted 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 these are misreported in DealScan as new loans, but they do not necessarily involve new money. Finally, we categorize loans as a credit line, term A, B, C, D, and E and exclude term loans B because banks hold none of these loans after the syndication. Term loans B are structured specifically to institutional investors and almost entirely sold off in the secondary market.[5]

Because there is no common identifier between these datasets, we hand-match DealScan

[3]The loan syndication market can display some unique types of agency problems, stemming both from adverse selection and moral hazard. An adverse selection problem arises when the participant lenders do not have private information about the borrower's quality. A moral hazard problem emerges when lenders decide to sell in the secondary market parts of the loan to a "passive" lender whose incentives to monitor are reduced.

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

[5]In addition, we disentangle banks from non-banks. 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 *US 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 observations that are classified as a bank by DealScan but actually are not, such as the General Motors Acceptance Corporation (GMAC) Commercial Finance. For a similar strategy using the DealScan database see Lim, Minton and Weisbach (2014).

with Call Reports to enrich the bank's balance sheet information. The matching is initially done by a fuzzy merge algorithm based on names and locations and we manually review all matching results. This process links the DealScan's lender ID with the commercial bank ID (RSSD9001) and provides a unique linkage for each lender. With this linkage, we are able to match information from the FRB for the banks' M&A. Because call reports are available on a quarterly basis, we collapse the loan data set on a quarter level and we match the date of the loan deal with the relevant quarter. For example, we match all syndicated loans that were originated from January 1st to March 31st with the first quarter of that year of the Call Reports. Similarly, we obtain information for the financial statements of the firms and their industries from Compustat using the link provided by Chava and Roberts (2008).

Further, to construct a measure for the degree 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 reference priced.

Finally, to capture enforcement actions, we follow Delis, Staikouras and Tsoumas (2016) and use their data set from 1999 until 2010, which is constructed by screening the websites of the three agencies acting as the primary federal supervisor of all insured commercial and savings banks in the United States: the Federal Reserve System, the Federal Deposit Insurance Corporation (FDIC), and the Office of the Comptroller of the Currency (OCC). Delis, Staikouras and Tsoumas (2016) group the formal enforcement actions according to their rationale into a number of categories, mostly reflecting the action's severity and relation with safety and soundness issues. We include only actions related to the Basel Committee Core Principles for Effective Banking Supervision. These include 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.

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

3.2 Measuring Experience

We construct three measures of past experience in the credit market, namely *sector*, *firm*, and *bank* using variation at bank-sector, bank-firm, and bank-bank level, respectively.

$Sector^{Exper}_{b,s,t}$ is defined as the total credit (\$M) lent by bank b to firms operating in a two-digit SIC sector s at time t over the total lending (\$M) by bank b to all the sectors (S):

$$Sector^{Exper}_{b,s,t} = \frac{Loan^{b \to s}_t}{Total\ Loan^{b \to S}_t} \qquad . \tag{1}$$

This index ranges from zero to one, with higher values reflecting higher experience in the sector in which the firm operates. $Sector^{Exper}$ varies at bank-sector level.[6] De Jonghe, Dewachter, Mulier, Ongena and Schepens (2020) use data from the Belgian credit registry and define this measure as the bank's sectoral specialization. In what follows, we use sectoral experience and sectoral specialization interchangeably.

Following Bharath, Dahiya, Saunders and Srinivasan (2009), we construct two measures for the number of previous interactions (relationships) between a bank and a firm and between banks. *Firm experience (# loans)*$_{b,f,t}$ measures the number of loans that a lender b lent to firm f in the past five years prior to a current loan. Every time a new loan is originated 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 past lending relations.

Bank experience (# loans)$_{b,j,t}$ measures the number of loans that the lead arranger b syndicated with other lenders j prior to the current loan. 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-years rolling window without taking into account the roles that the two lenders took in previous loans. This measure will assign a greater overlap of previous experience when in the syndicate there are banks with a higher number of bilateral interactions (loan co-sharing). This index measures the importance of prior relationships among banks.

[6] For robustness, we use a similar approach to construct the one, three and four SIC digits classification.

3.3 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 across maturity, loan type and collateral. We control for these differences by adding the natural logarithm of loan *maturity*; a dummy variable equal to one if the loan is secured with *collateral*;[7] a dummy equal to one if the loan type is a term loan; a dummy equal to one if the loan is linked with financial covenants to control for unobservable borrower risk factors (Carey and Nini, 2007); and a dummy equal to one if *performance pricing* is included in the loan contract to control for the borrower's business prospects (Ross, 2010).

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

4 Methodology and Estimation

Based on our hypotheses in Section 2, we estimate three empirical models.

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

$$\begin{aligned} Prob(lead_{b,f,t}) = \alpha' + \lambda_1 * Sector^{Exper}_{b,s,t} + \lambda_2 * Firm^{Exper}_{b,f,t} + \lambda_3 * Bank^{Exper}_{b,t} \\ + \beta_1 * L_{l,t} + \beta_2 * F_{f,t-1} + \epsilon_{b,f,t} \end{aligned} \quad (2)$$

where *lead* equals one when bank b is a lead arranger to a loan granted to firm f at time t, zero otherwise.[8] The sample set for equation 2 includes all banks that have been at least

[7] 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)

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

once a lead arranger in the last five years up to the date that the loan is granted. The timing of the variables is in line with the idea that a firm with certain characteristics at time $t-1$ will seek to obtain a loan at time t. The main independent variables are the sectoral, firm, and bank experience and their coefficients (λ_1, λ_2 and λ_3) reflect the change in the propensity to act as a lead arranger. $\alpha^{'}$ denotes different levels of time invariant and time varying fixed effects (more details later on). L and F are several loan and firm control variables, while ϵ is a loan-level idiosyncratic disturbance.

Second, we examine how experience influences the share (in percentage) held by bank b in the syndicated loan to firm f at time t (intensive margin). The fielded empirical model is:

$$Shares(\%)_{b,f,t} = \alpha^{'} + \lambda_1 * Sector^{Exper}_{b,s,t} + \lambda_2 * Firm^{Exper}_{b,f,t} + \lambda_3 * Bank^{Exper}_{b,t} + \beta_1 * L_{l,t} + \beta_2 * F_{f,t-1} + \epsilon_{b,f,t} \quad (3)$$

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

$$Conditional\ Shares(\%)_{b,f,t} = \alpha^{'} + \lambda_1 * Sector^{Exper}_{b,s,t} + \lambda_2 * Firm^{Exper}_{b,f,t} + \lambda_3 * Bank^{Exper}_{b,t} + \beta_1 * L_{l,t} + \beta_2 * F_{f,t-1} + \epsilon_{b,f,t} \quad (4)$$

An identification challenge in the empirical models, is that λ_1, λ_2 and λ_3 may be biased due to bank or industry unobservable characteristics. In particular, omitted variable bias is a concern because sectoral, firm, and bank experience may be driven by unobserved characteristics that also explain variation in lead propensity, shares (%) and conditional shares (%). However, our loan-level granularity helps us to overcome this issue through the inclusion of several fixed effects. Bank and industry (at the 3-digit SIC) fixed effects control for bias that could result from time-invariant bank and industry characteristics. Also, the inclusion of year fixed effects accounts for annual common shocks and insulates our model from differences between loans due to a time trend.

In addition, following Giannetti and Saidi (2019), we isolate simultaneous changes in credit supply and industry demand by inserting bank-year and industry-year fixed effects. These fixed effects control for time-varying unobservable bank fundamentals (such as profitability, risk, and other balance sheet characteristics) and industry fundamentals (e.g., future perspectives, forecast analyst, profitability, and other common characteristics). Essentially, we compare the same bank lending to different firms, while we control for the demand of the industry. In some more restrictive samples, we use bank-industry fixed effects to control for unobserved time-invariant characteristics such as location or distance.

Fixed effects account for omitted factors, but to further mitigate any lingering endogeneity concerns, we conduct an instrumental variables (IV) estimation in Section 5.2. Specifically, we exploit M&A's between banks that are active in the syndicated market as a plausibly exogenous shock (Favara and Giannetti, 2017). We construct instruments for sectoral, firm, and bank experience using only the historical experience variables of the target's bank (acquired). Our instruments are defined within a year, starting when a merger occurs until the new loan origination. The instruments are equal to zero before the merger.

5 Main Results

5.1 Baseline Estimates

Table 3 presents the results for the impact of the measures of banks' past experience on the extensive margin of syndicated loans. Consistent with the hypotheses in Section 2, we estimate a positive impact of all measures of experience on the probability of being a lead arranger. The results are robust across specifications, and remain unaltered when we saturate the regression with different levels of fixed effects, as noted at the bottom of the table. For example, column IV suggests that a one standard deviation increase in sectoral experience (14.4%) raises the probability of being a lead arranger by 3%. In turn, an increase in firm experience by one loan raises the probability of being a lead arranger by 15%.

In Tables 4 and 5, we turn to investigate the impact of banks' past experience on the intensive margin of syndicate participation and the share of the lead arranger. In Table 4 the dependent variable is the share of every arranger. The estimates thus nest together the effect of banks' experience on the decision to be a lead arranger and on the share of the loan retained by the banks. All types of experience appear to boost this measure of banks' involvement in syndicates.

A drawback of the estimates in Table 4 is that they do not separate extensive from intensive margin effects. In Table 5 we seek to disentangle the two margins. To this end, we report the results obtained by dropping from the sample the banks that are not lead arrangers, and focus solely on lead arrangers. This gives us an estimate of the impact of prior experience on the lead arranger's share, conditional on being a lead arranger. When we consider the impact of the various types of experience on the intensive margin of syndicate participation, we obtain strikingly different effects across types of experience. While sectoral experience increases the loan share retained by the lead arranger, firm and bank experience appear to shrink it. In addition, the impact of sectoral experience is sizeable: a one standard deviation increase in sectoral experience raises the lead share by 3.5 percentage points. The negative effects of firm and bank experience turn out to be economically less sizeable but highly statistically significant.

Recall that the lead share is interpreted as a proxy for the degree of moral hazard within a lending syndicate. Thus, the estimates suggest that moral hazard within syndicates may be more severe when the lead arranger has stronger sectoral experience. We conjecture that this could be due to the lead arranger having a larger outside option in the event of loan default and that this could dilute its incentive to monitor the loan. This is reminiscent of the argument in Manove, Padilla and Pagano (2001) that banks can become lazy monitors when they feel protected by firms' posting of collateral or, more in general, when their outside option is more valuable.

5.2 IV Estimates

In the baseline results, we saturate the empirical model with a full set of fixed effects and also control for a broad range of firm and loan characteristics. One may wonder whether our results are driven by sectoral, firm, and bank experience or if these variables reveal a bias because they are simultaneously pre-determined with syndicated lending practices. In this subsection, we adopt an instrumental-variables (IV) methodology to address this concern.

To yield exogenous variation in the experience variables that can help us to overcome remaining endogeneity issues, we follow Favara and Giannetti (2017) and exploit mergers between banks that are active in the syndicated loan market. To this end, we collect data on M&A's from the FED and identify the banks in DealScan. Then, we construct instruments for sectoral, firm, and bank experience using only the historical experience variables of the target bank (acquired). We restrict attention to mergers occurred in a window of one year preceding the origination of the syndicated loan. We also include bank, year and sector-year fixed effects. In this set up, we effectively exploit variation between banks, while controlling for the industry-loan level demand and the bank's balance sheet.

We exploit variation in our experience variables that is due to a recent merger. So, we identify a treatment effect using only information from the target bank. The validity of an IV approach depends on the quality of the instruments. Our instruments are likely to satisfy the relevance criterion because a merger constitutes a relevant shock to the acquirer's bank portfolios. When a bank acquires another bank, its portfolio of loans will subsequently incorporate the loans previously extended by the acquired bank, thus exogenously broadening the set of experience of the acquiring bank. In addition, it seems less likely that the target's sectoral-firm-and-bank experience affects the acquirer's bank lending decision due to the nature and size of these mergers.

Table 6 shows the results from the two-stages least square estimation with different levels of fixed effects, as noted in the lower part of the table. In columns I-III, IV-VI, and VII-IX, we replicate the baseline equations using instruments for the sectoral, firm, and bank experience, respectively. The first stage coefficient estimates in panel A are highly statistically significant and in line with the literature. In addition, the over-and-weak identification tests show that there are no concerns regarding the instrument validity. Panel B presents the second stage estimates using the estimated values. The second stage estimates are qualitatively and quantitatively similar to the baseline estimates.

6 Mechanisms

The results in Tables 3 - 6 suggest that the type of experience accumulated by lenders matters for the intensive and extensive margins of syndicates. In what follows we dig deeper into the data and exploit cross-sectional variation in various dimensions. The goal is twofold. We aim at verifying that the estimated effects of (our proxies for) bank experience are indeed driven by prior knowledge and information accumulated by lenders in lending syndicates. We are also interested in dissecting the scenarios in which bank experience is more likely to affect lending syndicates. Such findings should further create confidence in our identification strategy and mitigate concerns about omitted variables.

6.1 Sectoral Complexity

In Table 7, we exploit data on the informational complexity of the products produced in the sectors to better disentangle the role of experience, especially sectoral experience. We employ a measure of 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 created a concordance using information from OECD and Muendler (2009) to harmonize between SITC and SIC. The objective is to create a many-to-one mapping (from SITC to SIC) and, hence, in some cases we needed to 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).[9] In short, a firm is considered to be "heterogeneous" if the produced product is neither sold on an exchange nor reference priced. Among the loans in our sample 30% are linked with firms with heterogeneous products, a figure in line with Campello and Gao (2017). An industry with a higher share of heterogeneous products is more likely to be subject to informational frictions. Thus, we expect that banks' sectoral experience has a stronger marginal impact in such an industry, relative to an industry with less complex products.

The estimates indeed confirm that the effect of banks' sectoral experience is stronger for industries characterized by higher informational complexity. For example, column II of Table 7 reveals that higher past sectoral experience in industries with heterogeneous products increases the probability that a bank active in the syndicated market will act as the lead arranger by about 20%, while the baseline results suggest an increase of 12% (column V, Table 3). On the other hand, we find no significant difference between informationally complex and non-complex industries when considering the impact of firm and bank experience. This is line with expectations, as the informational complexity of a sector is plausibly more relevant for the impact of sectoral experience than for that of firm or bank experience.

[9] 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.

6.2 Firm-level Heterogeneity

A further way to ascertain that the baseline results indeed capture the influence of bank experience is to exploit the rich firm-level heterogeneity in our data. In Table 8, we subsample firms based on their profitability and degree of informational opaqueness and explore whether the effects of banks' experience differ depending on firms' sensitivity to banks' information. As indicators of firm profitability we consider the firm's Tobin q, while for informational opaqueness we consider external debt. We obtain that the impact of all types of experience on the probability of being a lead arranger is stronger for less profitable firms (lower Tobin's q). Regarding firms' external debt, the effects of banks' experience are significantly stronger for firms with less external debt. This is in line with the hypothesis that such firms are those more likely to benefit from banks' experience in that they less heavily rely on bank financing.

6.3 Bank-level Experience: Sectoral Specificity and Trust

The measure of bank-level experience investigated in the baseline tests can capture two forms of bank-level experience acquired by lenders. If a lending syndicate includes banks that are specialized in the same sector(s), then a bank can further enhance its sectoral information gathering through its interaction with the other banks in the syndicate and gain the ability to coordinate with them in extending loans to firms of the sector. If instead the other banks in the syndicate are specialized in other sectors, experience could especially take the form of trust and direct acquaintance with those banks, rather than sectoral knowledge. We then separate our measure of bank-level experience between the number of prior loans that involve banks lending to the same sectors and to different sectors.

In Table 9, we report the results for the impact of prior experience on the lead lender's share. The data suggest that lead arrangers tend to syndicate loans with banks that have prior experience in the same sectors. In columns I-II, we restrict our measure of bank experience only to loans to the same sectors while in columns III-IV we use the bank experience excluding loans to the same sectors. The estimated coefficients on sectoral experience and firm experience are in line with the results in Table 5. Interestingly, the estimates suggest that the effect of bank-specific experience stems from sector familiarity instead of a trust effect (compare columns I-III and II-IV). In column I, we explore within-bank variation and find that the loan share retained by the lead arranger decreases by one percentage point when we include only loans to the same sectors. In column II, we use a conservative specification and repeat the same analysis but this time we include bank-industry fixed effects, obtaining similar results. In column III, the bank experience variable takes variation only from different sectors: the estimated coefficient is statistically insignificant and becomes significant at the 10% level when we add the bank-industry fixed effects (column IV). However, the economic significance of the bank-level experience is economically less sizeable compared to columns I and II.

In columns V to VIII, we repeat the same analysis only for industries with heterogeneous products. We find that the effect of bank experience including the same sectors is qualitatively and quantitatively similar with respect to columns I and II. On the other hand, bank experience excluding the same sectors is significant at the 5% level in column VII but becomes insignificant when we control for the bank-industry matching (column VIII). Notably, the effect on sectoral and firm experience is insignificant because firm and sector variation for heterogeneous product is constant and the value added of additional loans is limited.

6.4 Experience and Reputation Shocks

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

To measure the *post-sanction* variable, we reconstruct the syndicated loan market on a bank-bank basis and identify active lead arrangers that received an enforcement action. In turn, we track the historical records of the participants that were linked in syndicated deals with the punished lead banks. The *post-sanction* variable is defined as an indicator that equals one if the new lead arranger in a current loan was cooperating from a participant role with the punished bank in past transactions. In this analysis, we use a rich set of sanctions as a stigma on bank's reputation to analyze which bank will replace the punished lead arranger.

The results are shown in Table 10. Our regression sample includes a treated group of prior lead arrangers that received a sanction and a control group for lead arrangers without a sanction. This regression is then similar to a treatment effects model. We find that the probability of being the lead arranger, the retained allocation (%), and the lead retained allocation (%) increase following the *post-sanction* for higher sectoral, firm, and bank experience. These findings are consistent with the hypothesis that indeed experience enhances the flexibility with which a bank can replace a co-lender hit by a reputation shock. They also confirm that our proxies are effectively picking up the impact of banks' experience in the credit market.[10]

7 Robustness and Extensions

7.1 Robustness Tests

In Table 11, we conduct a variety of robustness tests. In columns I-III we keep data only for loans in which the syndicate members (banks and firm) are repeated. This allows for a powerful test because, given the inclusion of bank-year fixed effects, only the time variation on experience variables will play a role in driving the dependent variable. The results are very close to those of the baseline specifications, showing that our findings are robust to concerns arising from differences in the structure of the syndicate.

In columns IV-VI we exclude NBER recessions, as defined by the NBER's Business Cycle Dating Committee. In columns VII-IX, 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 allows to verify that the results are not driven solely by the efficiency of the very large banks in originating large loan deals.

In Table 12, we experiment with an alternative indicator that is sometimes used to capture a lenders' information advantage in extending loans, the banks' sectoral market share. We follow De Jonghe, Dewachter, Mulier, Ongena and Schepens (2020) and calculate the sectoral shares as the amount ($M) lent by bank b to a firm classified in a two-digit

[10] Apart from loss of reputation, a sanction may also lead to an erosion in a lead arranger's syndicated lending activity (Delis, Staikouras and Tsoumas, 2016). In Appendix A1, we observe that punished banks reduce lending in the commercial market.

SIC sector s at time t over the total credit of the sector (s):

$$Sector_{b,s,t}^{Shares} = \frac{Loan_t^{b \to s}}{Total\ Loan_t^s}$$

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

In the Appendix section, Table A2, we present further sensitivity analysis using the one-three-and-four digits industry classifications to measure the sectoral experience. The results are qualitatively similar to the baseline. However, as expected, the economic significance of the estimated coefficients of interest increases as we use a more disaggregate SIC classification. In addition, the theoretical considerations discussed above, especially those in Boot and Thakor (2000), suggest that there may be a non-linear relation in banks learning by experience. To this end, in Table A3, we examine whether the effect of different dimensions of the bank's experience is non-linear by adding its squared term. Our results indeed indicate a non-linear effect and suggest an inverted U-shape relation between the bank's experience in all measures (*sector, firm and bank*) and the intensive and extensive margin.

7.2 Firm Outcomes

Having established that the association between banks' experience and their lending decision is robust, in this section we explore the effects of banks' experience on firm outcomes in the year after the loan origination. Table 13 displays the results. In this set up, we are mainly concerned with the matching of firm outcomes at *t+1* and not with the identification of a causal relation running from the experience variables to firm outcomes. Thus, we are interested only in reducing the omitted-variable bias by inserting bank-year and industry-year fixed effects to saturate credit supply and industry demand factors. In the regressions we include loan control variables and the lagged dependent variable (at time t) as an explanatory variable of *t+1* in order to capture persistence. In all specifications, the coefficient on the lagged dependent variable is positive and statistically significant.

In column I of Table 13, the dependent variable is the natural logarithm of the firm's total assets at *t+1*. We observe that the sector and bank experience have a positive and significant effect on the firm's size. Specifically, the point estimate suggests that a standard deviation increase in sectoral experience is associated with an increase in the firm's size by 14 percentage points. This is consistent with theories in which closer monitoring by lenders has a positive impact on future firm performance (Boot and Thakor, 2000). However, we also find that firm experience has a negative and significant effect on the firm's size, though the effect is economically less sizeable.[11] In the rest of the tests, we find qualitatively and quantitatively similar estimates when we use as a dependent variable *sales* as a proxy for firm's efficiency (column II), *ROA* as a proxy for firm's profitability (column III) and a *dividend* dummy equal to one if a firm distributes a dividend in the year after the loan origination (column IV).

8 Conclusions

Experience is traditionally viewed as a fundamental mechanism of acquisition of information and knowledge in the banking sector. The way credit market experience influences the monitoring activity of banks, and hence the extent of moral hazard issues, is however relatively under-explored. Experience can reduce the costs of monitoring borrowers, thus incentivizing banks' monitoring effort. It can, nonetheless, also improve banks' outside option in the event of inadequate monitoring, thereby diluting banks' monitoring incentives. To resolve this ambiguity, in this paper we study the impact on credit market outcomes of three forms of experience accumulated by banks: sectoral experience, experience on borrowing firms, and experience on co-lender banks.

The results suggest that both experience on borrowers and experience on co-lenders incentivize banks' screening and monitoring effort, mitigating moral hazard issues in lending syndicates. By contrast, in our data we find evidence that sectoral experience exacerbates moral hazard issues. Exploiting cross-section heterogeneity across firms and banks, we further uncover that the dilution of banks' monitoring incentives induced by sectoral experience is particularly pronounced for industries and products with high information complexity. On the other hand, the incentivizing impact of experience on borrowers and

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

co-lenders on banks' monitoring effort manifests itself especially for less profitable and more informationally opaque firms.

In the paper 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 banks' experience can yield new insights into the role of banks in the aftermath of shocks. We leave this and other relevant issues to future research.

References

Adams, R. B. and Ferreira, D. (2009), 'Women in the boardroom and their impact on governance and performance', *Journal of Financial Economics* **94**, 291–309.

Agarwal, S. and Hauswald, R. (2010), 'Distance and private information in lending', *The Review of Financial Studies* **23**(7), 2757–2788.

Berger, A. N. and Udell, G. F. (1990), 'Collateral, loan quality and bank risk', *Journal of Monetary Economics* **25**, 21–42.

Bharath, S. T., Dahiya, S., Saunders, A. and Srinivasan, A. (2009), 'Lending relationships and loan contract terms', *The Review of Financial Studies* **24**(4), 1141–1203.

Boot, A. W. (2000), 'Relationship banking: What do we know?', *Journal of Financial Intermediation* **9**(1), 7 – 25.

Boot, A. W. and Thakor, A. V. (2000), 'Can relationship banking survive competition?', *The Journal of Finance* **55**(2), 679–713.

Botsch, M. and Vanasco, V. (2019), 'Learning by lending', *Journal of Financial Intermediation* **37**, 1–14.

Caballero, J., Candelaria, C. and Hale, G. (2018), 'Bank linkages and international trade', *Journal of International Economics* **115**, 30–47.

Campello, M. and Gao, J. (2017), 'Customer concentration and loan contract terms', *Journal of Financial Economics* **123**(1), 108–136.

Carey, M. and Nini, G. (2007), 'Is the corporate loan market globally integrated? a pricing puzzle', *The Journal of Finance* **62**(6), 2969–3007.

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

Darmouni, O. (2020), 'Informational frictions and the credit crunch', *The Journal of Finance* **75**(4), 2055–2094.

De Jonghe, O., Dewachter, H., Mulier, K., Ongena, S. and Schepens, G. (2020), 'Some borrowers are more equal than others: Bank funding shocks and credit reallocation', *Review of Finance* **24**(1), 1–43.

Degryse, H. and Van Cayseele, P. (2000), 'Relationship lending within a bank-based system: Evidence from european small business data', *Journal of Financial Intermediation* **9**(1), 90–109.

Delis, M. D., Iosifidi, M., Kokas, S., Xefteris, D. and Ongena, S. (2020), 'Enforcement actions on banks and the structure of loan syndicates', *Journal of Corporate Finance* **60**, 101527.

Delis, M. D., Kokas, S. and Ongena, S. (2017), 'Bank market power and firm performance', *Review of Finance* **21**, 299.

Delis, M. D., Staikouras, P. K. and Tsoumas, C. (2016), 'Formal enforcement actions and bank behavior', *Management Science* **63**(4), 959–987.

Dennis, S. A. and Mullineaux, D. J. (2000), 'Syndicated loans', *Journal of Financial Intermediation* **9**, 404–426.

Diamond, D. W. (1991), 'Monitoring and reputation: The choice between bank loans and directly placed debt', *Journal of Political Economy* **99**(4), 689–721.

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

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

Giannetti, M. and Saidi, F. (2019), 'Shock propagation and banking structure', *The Review of Financial Studies* **32**(7), 2499–2540.

Habib, M. A. and Johnsen, D. B. (1999), 'The financing and redeployment of specific assets', *The Journal of Finance* **54**(2), 693–720.

Ioannidou, V. and Ongena, S. (2010), '"time for a change": loan conditions and bank behavior when firms switch banks', *The Journal of Finance* **65**(5), 1847–1877.

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

Ivashina, V. and Scharfstein, D. (2010), 'Bank lending during the financial crisis of 2008', *Journal of Financial Economics* **97**, 319–338.

Iyer, R., Khwaja, A. I., Luttmer, E. F. and Shue, K. (2016), 'Screening peers softly: Inferring the quality of small borrowers', *Management Science* **62**(6), 1554–1577.

Jiménez, G., Ongena, S., Peydró, J.-L. and Saurina, J. (2014), 'Hazardous times for monetary policy: What do twenty-three million bank loans say about the effects of monetary policy on credit risk-taking?', *Econometrica* **82**(2), 463–505.

Jiménez, G., Ongena, S., Peydró, J.-L. and Saurina, J. (2017), 'Macroprudential policy, countercyclical bank capital buffers, and credit supply: evidence from the spanish dynamic provisioning experiments', *Journal of Political Economy* **125**(6), 2126–2177.

Liberti, J. M. and Petersen, M. A. (2019), 'Information: Hard and soft', *Review of Corporate Finance Studies* **8**(1), 1–41.

Lim, J., Minton, B. A. and Weisbach, M. S. (2014), 'Syndicated loan spreads and the composition of the syndicate', *Journal of Financial Economics* **111**, 45–69.

Manove, M., Padilla, A. J. and Pagano, M. (2001), 'Collateral versus project screening: A model of lazy banks', *The RAND Journal of Economics* **32**(4), 726–744.

Muendler, M.-A. (2009), 'Converter from sitc to isic', *University of California-San Diego, unpublished mimeo* .

Ongena, S. and Smith, D. C. (2000), 'What determines the number of bank relationships? cross-country evidence', *Journal of Financial Intermediation* **9**(1), 26–56.

Rajan, R. G. (1992), 'Insiders and outsiders: The choice between informed and arm's-length debt', *The Journal of Finance* **47**(4), 1367–1400.

Rajan, R. and Winton, A. (1995), 'Covenants and collateral as incentives to monitor', *The Journal of Finance* **50**(4), 1113–1146.

Rauch, J. E. (1999), 'Networks versus markets in international trade', *Journal of International Economics* **48**(1), 7–35.

Roberts, M. R. (2015), 'The role of dynamic renegotiation and asymmetric information in financial contracting', *Journal of Financial Economics* **116**(1), 61–81.

Roberts, M. R. and Sufi, A. (2009), 'Renegotiation of financial contracts: Evidence from private credit agreements', *Journal of Financial Economics* **93**(2), 159–184.

Ross, D. G. (2010), 'The "dominant bank effect:" how high lender reputation affects the information content and terms of bank loans', *The Review of Financial Studies* **23**(7), 2730–2756.

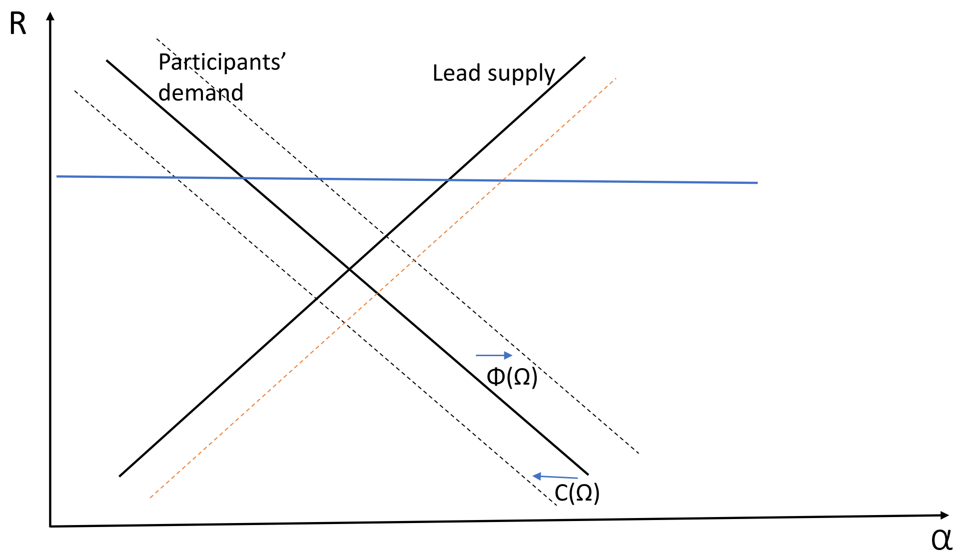
Schwert, M. (2018), 'Bank capital and lending relationships', *The Journal of Finance* **73**(2), 787–830.

Shleifer, A. and Vishny, R. W. (1992), 'Liquidation values and debt capacity: A market equilibrium approach', *The Journal of Finance* **47**(4), 1343–1366.

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

Figures

Figure 1: Supply and demand curve



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

Tables

Table 1: Variables definition and sources

Name	Description	Source
Dependent variables:		
Lead bank	Dummy variable equal to one if the bank is acting as a lead manager and zero otherwise.	DealScan
Lender shares (%)	The share of the loan held by lender.	DealScan
Main explanatory variable:		
Sector experience (SIC2)	$Sector^{Exper}_{b,s,t} = \frac{Loan^{b \rightarrow s}_t}{Total\ Loan^{b \rightarrow S}_t}$, the amount (\$M) lent by bank b to a firm classified on a two-digit SIC sector s at time t over the total amount of lending (\$M) lent by bank b to the total number of sectors (S). This index ranges from zero to one, with higher values reflecting higher exposure in the sector that the firm operates. Similar construction for the one, three and four SIC digits.	Own calculations
Firm experience (# loans)	The number of loans that a bank lent to the same borrower in the past five years prior to a current loan.	Own calculations
Bank experience (# loans)	The average number of loans that the lead arranger syndicated with participant lenders prior to a current loan.	Own calculations
Loan-level explanatory variables:		
Maturity	The natural logarithm of loan maturity in months.	DealScan
Collateral	Dummy variable equal to one if the loan is secured with collateral and zero otherwise.	DealScan
Term	Dummy variable equal to one if the loan type is a term loan.	DealScan
General covenants	The number of general covenants (intensity), taking values from zero to nine.	DealScan
Performance pricing	Dummy variable equal to one if the loan has performance pricing provisions and zero otherwise.	DealScan
Firm-level explanatory variables:		
Tobin's q	The natural logarithm of market-to-book value.	Compustat
ROA	Return on assets.	Compustat
Firm size	The natural logarithm of firm's total assets.	Compustat
Dividend	Dummy variable equal to one if a firm provided a dividend payout policy.	Compustat

Bank-level explanatory variables:		
Total Loans	The fraction of total loans over total assets .	Call reports
Deposits	The fraction of total deposits over total assets.	Call reports
Tier1	The fraction of tier 1 capital over total assets.	Call reports
NPLs	Non-performing loans.	Call reports
HHI-deposits	Deposits HHI.	Call reports
Cross-sectional variation:		
Sanction	Dummy variable equal to one when an enforcement action is imposed on a bank and zero otherwise. The enforcement actions include all actions (penalties) enacted on banks for breaches of laws and regulations in a number of cases. These cases include laws and regulations related to the Basel Committee Core Principles for Effective Banking Supervision (i.e., capital adequacy and liquidity, asset quality, provisions and reserves, large exposures and exposures related to parties, internal control and audit systems, money laundering, bank secrecy, consumer protection, and foreign assets control). They also include breaches of the requirements concerning the fitness and propriety of banks' board members and senior management, as well as other persons closely associated with banks (institution affiliated parties).	FED, FDIC, and OCC
Post-sanction	Dummy variable equal to one when a bank participated in a previous syndicated loan and the lead arranger received a regulatory enforcement action.	Own calculations
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 differentiated goods for which branding information precludes them from being traded on exchanges or reference priced.	Rauch (1999)
Sectoral shares (SIC2)	$Sector^{Shares}_{b,s,t} = \frac{Loan^{b \rightarrow s}_t}{Total\ Loan^s_t}$, the amount (\$M) lent by bank b to a firm classified on a two-digit SIC sector s at time t over the total credit of the sector (s). This index ranges from zero to one, with higher values reflecting higher concentration.	Own calculations

Table 2: Summary statistics

Variables	Level	Obs.	Mean	Std. Dev.	Min.	Median	Max.
Panel A: Summary statistics							
Lead bank	Bank	61,932	0.243	0.429	0.000	0.000	1.000
Lender shares (%)	Bank	61,932	19.610	25.877	0.000	10.000	100
Sectoral experience (SIC1)	Bank	61,932	0.177	0.158	0.000	0.138	1.000
Sectoral experience (SIC2)	Bank	61,932	0.075	0.144	0.000	0.031	1.000
Sectoral experience (SIC3)	Bank	61,932	0.055	0.136	0.000	0.013	1.000
Sectoral experience (SIC4)	Bank	61,932	0.051	0.134	0.000	0.010	1.000
Firm experience (# loans)	Bank	61,932	0.238	0.981	0.000	0.000	35.000
Bank experience (# loans)	Bank	61,932	0.586	3.222	0.000	0.000	72.000
Maturity	Loan	61,932	3.587	0.740	-2.708	3.871	5.892
Collateral	Loan	61,932	0.376	0.484	0.000	0.000	1.000
Term	Loan	61,932	0.071	0.258	0.000	0.000	1.000
General covenants	Loan	61,932	2.419	2.603	0.000	2.000	9.000
Performance pricing	Loan	61,932	0.507	0.500	0.000	1.000	1.000
Tobin's q	Firm	61,932	1.740	2.367	0.335	1.423	203.467
ROA	Firm	61,932	0.022	0.305	0.000	0.009	31.335
Firm size	Firm	61,932	7.242	1.824	-1.966	7.232	14.571
Dividend	Firm	61,932	0.583	0.492	0.000	1.000	1.000
Total loans	Bank	61,932	0.587	0.155	0.000	0.611	1.055
Deposits	Bank	61,932	0.605	0.194	0.000	0.648	0.984
Tier1	Bank	42,040	0.076	0.042	0.000	0.068	0.980
NPLs	Bank	61,908	0.009	0.016	0.000	0.000	0.271
HHI-deposits	Bank	61,932	0.019	0.014	0.005	0.019	0.058
Sanction	Bank	34,012	0.103	0.304	0.000	0.000	1.000
Post-sanction	Loan	28,237	0.054	0.226	0.000	0.000	1.000
Product complexity	Firm	21,961	0.300	0.100	0.000	0.000	1.000
Sectoral shares (SIC2)	Bank	61,932	0.229	0.261	0.000	0.118	1.000
Panel B: Variation for the main variables of interest							
	Between	Within					
Sectoral exposure (SIC2)	0.356	0.099					
Firm experience (# loans)	0.238	0.955					
Bank experience (# loans)	0.371	3.030					

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

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

	I	II	III	IV	V
Sectoral experience (SIC2)	0.217***			0.188***	0.121***
	[5.511]			[5.724]	[4.669]
Firm experience (# loans)		0.162***		0.156***	0.132***
		[16.964]		[17.896]	[15.646]
Bank experience (# loans)			0.023***	0.018***	0.015***
			[4.819]	[4.580]	[5.131]
Maturity	-0.057***	-0.046***	-0.056***	-0.046***	-0.042***
	[-11.045]	[-8.421]	[-10.993]	[-8.397]	[-8.757]
Collateral	0.051***	0.042***	0.053***	0.042***	0.032***
	[7.527]	[6.518]	[7.894]	[6.619]	[4.874]
Term	0.053***	0.040***	0.054***	0.043***	0.038***
	[6.336]	[4.771]	[6.243]	[5.052]	[4.265]
General covenants	-0.022***	-0.021***	-0.022***	-0.021***	-0.016***
	[-11.074]	[-10.651]	[-11.175]	[-10.863]	[-8.818]
Performance pricing	-0.041***	-0.030***	-0.043***	-0.031***	-0.027***
	[-6.487]	[-4.990]	[-7.064]	[-5.383]	[-4.389]
Tobin's q	-0.001	-0.001	-0.001	-0.001	-0.001
	[-1.497]	[-0.871]	[-1.449]	[-0.889]	[-1.208]
ROA	0.003	0.002	0.003	0.002	0.003
	[0.573]	[0.554]	[0.527]	[0.583]	[0.711]
Firm size	-0.084***	-0.081***	-0.084***	-0.082***	-0.077***
	[-10.321]	[-12.521]	[-10.352]	[-12.493]	[-10.045]
Observations	60,148	60,148	60,148	60,148	56,060
R-squared	0.360	0.475	0.381	0.489	0.537
F-test	65.80	153.1	68.38	153.6	189.8
Year FE					Y
Industry(SIC3)*Year FE	Y	Y	Y	Y	
Bank*Year FE	Y	Y	Y	Y	
Bank*Industry(SIC3) FE					Y
Clustered standard errors	Bank	Bank	Bank	Bank	Bank

The table reports coefficients and t-statistics (in brackets) for lenders that have been the lead arranger at least once within the last 5 years up to the date that a loan is announced. We estimate the regression:

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

where b, s, f, t refer to bank, sector, firm and year, respectively. We estimate this regression on a loan-level sample originated from 1987 to 2014. All variables are defined in Table 1. All specifications are estimated with a linear probability model specification 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 lender shares (%)

	I	II	III	IV	V
Sectoral experience (SIC2)	15.759***			15.498***	12.702***
	[7.748]			[7.690]	[6.264]
Firm experience (# loans)		1.778***		1.816***	1.434***
		[5.006]		[4.907]	[3.811]
Bank experience (# loans)			-0.128***	-0.182***	-0.224***
			[-4.475]	[-5.588]	[-6.711]
Maturity	-5.980***	-5.843***	-5.968***	-5.864***	-5.079***
	[-16.813]	[-16.596]	[-16.800]	[-16.617]	[-13.004]
Collateral	3.981***	3.939***	4.037***	3.867***	2.732***
	[8.981]	[8.661]	[9.031]	[8.524]	[5.588]
Term	5.590***	5.385***	5.506***	5.443***	4.886***
	[8.596]	[8.129]	[8.377]	[8.310]	[7.535]
General covenants	-2.214***	-2.195***	-2.213***	-2.193***	-1.809***
	[-15.235]	[-14.974]	[-15.107]	[-15.124]	[-12.201]
Performance pricing	-5.021***	-4.907***	-5.026***	-4.879***	-4.371***
	[-11.527]	[-11.296]	[-11.574]	[-11.299]	[-10.899]
Tobin's q	-0.097***	-0.091***	-0.096***	-0.092***	-0.091**
	[-3.222]	[-3.151]	[-3.200]	[-3.168]	[-2.562]
ROA	-0.351***	-0.368***	-0.362***	-0.354***	0.080
	[-3.176]	[-3.253]	[-3.172]	[-3.184]	[0.424]
Firm size	-8.236***	-8.155***	-8.184***	-8.199***	-7.749***
	[-20.177]	[-20.939]	[-20.156]	[-20.990]	[-17.724]
Observations	60,148	60,148	60,148	60,148	56,060
R-squarred	0.595	0.597	0.593	0.599	0.586
F-test	101	111.6	100.3	93.59	137.5
Year FE					Y
Industry(SIC3)*Year FE	Y	Y	Y	Y	
Bank*Year FE	Y	Y	Y	Y	
Bank*Industry(SIC3) FE					Y
Clustered standard errors	Bank	Bank	Bank	Bank	Bank

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

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

where b, s, f, t refer to bank, sector, firm and year, respectively. We estimate this regression on a loan-level sample originated from 1987 to 2014. All variables are defined in Table 1. All specifications include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. 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 lead lender shares (%)

	I	II	III	IV	V
Sectoral experience (SIC2)	24.806***			24.467***	25.756***
	[3.630]			[3.637]	[5.479]
Firm experience (# loans)		-1.031***		-1.027***	-0.522***
		[-6.113]		[-5.999]	[-3.408]
Bank experience (# loans)			-0.738**	-0.737**	-0.593***
			[-2.486]	[-2.483]	[-3.053]
Maturity	-7.638***	-7.739***	-7.617***	-7.729***	-7.342***
	[-13.301]	[-13.409]	[-13.341]	[-13.526]	[-13.011]
Collateral	4.683***	4.851***	4.521***	4.450***	4.264***
	[6.631]	[6.952]	[6.146]	[6.177]	[5.315]
Term	9.090***	9.109***	8.743***	8.870***	8.159***
	[9.288]	[9.368]	[8.861]	[9.260]	[9.364]
General covenants	-2.771***	-2.734***	-2.692***	-2.665***	-2.274***
	[-8.127]	[-7.939]	[-7.939]	[-7.928]	[-6.108]
Performance pricing	-6.307***	-6.392***	-5.940***	-6.111***	-5.588***
	[-4.788]	[-5.016]	[-4.640]	[-4.961]	[-4.367]
Tobin's q	-0.165*	-0.174**	-0.157*	-0.157*	-0.137*
	[-1.880]	[-2.017]	[-1.893]	[-1.880]	[-1.960]
ROA	-0.658***	-0.648***	-0.601***	-0.614***	0.026
	[-3.256]	[-3.124]	[-2.893]	[-3.139]	[0.061]
Firm size	-9.129***	-8.791***	-8.792***	-8.627***	-8.343***
	[-12.551]	[-12.448]	[-12.403]	[-12.643]	[-10.472]
Observations	16,101	16,101	16,101	16,101	16,144
R-squarred	0.694	0.695	0.700	0.703	0.680
F-test	136.9	132.4	157.6	145	270
Year FE					Y
Industry(SIC3)*Year FE	Y	Y	Y	Y	
Bank*Year FE	Y	Y	Y	Y	
Bank*Industry(SIC3) FE					Y
Clustered standard errors	Bank	Bank	Bank	Bank	Bank

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

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

where b, s, f, t refer to bank, sector, firm and year, respectively. We estimate this regression on a loan-level sample originated from 1987 to 2014. All variables are defined in Table 1. All specifications include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. 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: Instrumental variables estimation using acquired (M&As) bank experience

	I	II	III	IV	V	VI	VII	VIII	IX
					Panel A: First-stage results				
Acquired sectoral experience (SIC2)	0.147***	0.147***	0.160***						
	(19.193)	(19.193)	(8.886)						
Acquired firm experience (# loans)				0.017***	0.017***	0.020*			
				(3.327)	(3.327)	(1.768)			
Acquired bank experience (# loans)							2.560***	2.560***	3.888***
							(13.658)	(13.658)	(8.067)
					Panel B: Second-stage results with fitted values per category				
Dependent variable:	Prob(lead)	Lender shares (%)	Lead lender shares (%)	Prob(lead)	Lender shares (%)	Lead lender shares (%)	Prob(lead)	Lender shares (%)	Lead lender shares (%)
Sectoral experience (SIC2)	0.159**	18.459***	27.114**	0.072***	5.935***	3.480	0.061***	6.423***	5.043
	(2.046)	(3.106)	(2.039)	(3.897)	(4.424)	(1.072)	(3.618)	(5.184)	(1.587)
Firm experience (# loans)	0.159***	4.028***	-1.320***	0.222***	10.269**	1.878	0.147***	2.306***	-2.036***
	(36.561)	(19.126)	(-7.152)	(2.915)	(2.139)	(0.294)	(29.305)	(13.355)	(-10.671)
Bank experience (# loans)	0.015***	-0.380***	-1.030***	0.016***	-0.453***	-1.234***	0.072***	0.901**	-3.018***
	(25.121)	(-15.511)	(-22.254)	(6.808)	(-3.132)	(-15.230)	(9.044)	(2.416)	(-4.350)
Loan controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	28,237	28,237	5,372	28,237	28,237	5,372	28,237	28,237	5,372
R-squared	0.391	0.369	0.554	0.374	0.282	0.530	0.256	0.341	0.515
F-stat	767.3	171.6	186.9	346.3	19.48	85.99	600.2	148.3	50.57
LM-test for under identification	343.3	343.3	81.79	12.84	12.84	4.658	202.3	202.3	81.40
F-stat for weak identification	368.4	368.4	78.96	11.07	11.07	3.127	186.5	186.5	65.08
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry (SIC3)*Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Clustered standard errors	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

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

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

where b, s, f, t refer to bank, sector, firm and year, respectively. We estimate this regression on a loan-level sample originated from 1987 to 2014. We report the first stage regressions in Panel A. The LM statistic is distributed as chi-square under the null that the equation is under-identified. The F-stat is distributed as chi-square under the null of exogeneity. All variables are defined in Table 1. All specifications include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. Standard errors are robust and clustered at the bank level. The *,**,*** marks denote the statistical significance at the 10, 5, and 1% level, respectively.

Table 7: Experience and product information complexity

	I	II	III	IV	V	VI
Dependent variable	Prob(lead)		Lender shares (%)		Lead lender shares (%)	
Group:	Complex	Non-complex	Complex	Non-complex	Complex	Non-complex
Sectoral experience (SIC2)	0.421***	0.176***	25.964***	15.337***	39.036**	28.273***
	[3.250]	[5.000]	[3.715]	[6.904]	[2.271]	[3.513]
Firm experience (# loans)	0.170***	0.155***	1.513***	1.840***	-1.030**	-0.933***
	[11.504]	[18.594]	[2.766]	[5.392]	[-2.136]	[-4.140]
Bank experience (# loans)	0.016***	0.018***	-0.170***	-0.178***	-0.672***	-0.760**
	[3.805]	[4.712]	[-3.017]	[-5.595]	[-3.718]	[-2.503]
Loan controls	Y	Y	Y	Y	Y	Y
Firm controls	Y	Y	Y	Y	Y	Y
Observations	10,541	51,633	10,541	51,633	2,608	10,612
R-squared	0.517	0.492	0.629	0.598	0.748	0.710
F-test	67.25	141.1	50.16	84.83	50.98	113.4
Year FE		Y		Y		Y
Bank*Year FE	Y		Y		Y	
Industry*Year FE	Y		Y		Y	
Bank*Industry FE	N	Y		Y		Y
Clustered standard errors	Bank	Bank	Bank	Bank	Bank	Bank

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

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

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

Table 8: Sub-samples and firm heterogeneity

	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
Sub-sample:	Tobins q						External debt					
Dependent variable:	Prob(lead)		Lender shares(%)		Lead Lender shares(%)		Prob(lead)		Lender shares(%)		Lead Lender shares(%)	
Group:	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High
Sectoral experience (SIC2)	0.284***	0.158***	20.087***	13.569***	34.883***	23.417**	0.247***	0.168***	18.685***	14.388***	32.789***	31.745**
	[6.646]	[3.478]	[7.820]	[5.213]	[3.820]	[2.331]	[5.163]	[3.568]	[6.173]	[5.656]	[5.091]	[2.475]
Firm experience (# loans)	0.147***	0.173***	1.665***	1.788***	-0.978***	-0.768***	0.150***	0.169***	1.465***	1.720***	-0.625***	-1.395***
	[18.338]	[25.337]	[6.186]	[4.812]	[-2.799]	[-2.713]	[12.193]	[21.872]	[4.392]	[5.186]	[-3.151]	[-5.323]
Bank experience (# loans)	0.019***	0.017***	-0.124***	-0.146***	-0.781**	-0.628***	0.019***	0.018***	-0.164***	-0.120***	-0.732***	-0.568**
	[4.204]	[5.074]	[-2.695]	[-4.848]	[-2.131]	[-2.831]	[5.493]	[4.559]	[-5.285]	[-3.584]	[-2.917]	[-2.241]
Loan controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	24,668	34,060	24,668	34,060	5,921	8,385	25,722	23,562	25,722	23,562	6,427	5,180
R-squarred	0.518	0.525	0.636	0.648	0.737	0.747	0.534	0.524	0.692	0.617	0.781	0.726
F-test	93.09	188.6	61.26	115	84.13	111.1	119.7	100.4	73.29	73.17	107.6	93.02
Bank*Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry*Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Clustered standard errors	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

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

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

where b, s, f, t refer to bank, sector, firm and year, respectively. We estimate this regression on a loan-level sample originated from 1987 to 2014. All variables are defined in Table 1. All specifications include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. 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 9: Experience and sectoral similarity

	I	II	III	IV	V	VI	VII	VIII
Dependent variable	Lead lender shares (%)							
Group:					Sectors with information complexity			
Sectoral experience (SIC2)	15.724**	18.644***	24.947***	21.222***	-18.905	5.662	14.317	19.740*
	[2.275]	[3.965]	[6.068]	[3.958]	[-0.891]	[0.605]	[0.789]	[1.792]
Firm experience (# loans)	-1.093***	-0.282	-0.246**	-0.098	-0.580	-0.038	-0.402*	-0.214
	[-2.984]	[-1.010]	[-2.191]	[-0.866]	[-0.841]	[-0.091]	[-2.006]	[-1.281]
Bank experience (# loans for same sectors)	-0.930**	-0.818***			-0.728***	-0.735***		
	[-2.309]	[-2.793]			[-3.420]	[-3.615]		
Bank experience (# loans for different sectors)			-0.065	-0.052*			-0.133**	-0.089
			[-1.600]	[-1.898]			[-2.250]	[-1.189]
Loan controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	5,237	5,776	10,919	9,928	594	857	1,496	1,532
Adjusted R-squared	0.646	0.672	0.376	0.372	0.691	0.698	0.326	0.384
F-test	113.4	86.85	260.7	242.5	22.43	22.25	106.6	44.38
Year FE		Y		Y		Y		Y
Industry*Year FE	Y		Y		Y		Y	
Bank*Year FE	Y		Y		Y		Y	
Bank*Industry FE		Y		Y		Y		Y
Clustered standard errors	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

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

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

where b, s, f, t refer to bank, sector, firm and year, respectively. We estimate this regression on a loan-level sample originated from 1987 to 2014. The dependent variable is reported in the second line. In columns V-VIII we use a sub-sample only for firms that operates in industries with differentiated products (complex products) following Rauch (1999). All variables are defined in Table 1. All specifications include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. Standard errors are robust and clustered at the firm level. The *,**,*** marks denote the statistical significance at the 10, 5, and 1% level, respectively.

Table 10: Treatment group for post-sanction members

	I	II	III	IV	V	VI
Dependent variable	Prob(lead)		Lender shares (%)		Lead lender shares (%)	
Sectoral experience (SIC2)	0.188***	0.115***	14.904***	10.656***	11.780	16.425***
	[5.668]	[4.204]	[6.116]	[4.560]	[0.652]	[3.655]
Sectoral experience * Post-sanction	0.218***	0.120***	14.904***	10.656***	15.217**	16.425***
	[5.886]	[3.948]	[6.116]	[4.560]	[2.377]	[3.655]
Firm experience (# loans)	0.147***	0.124***	3.985***	3.637***	-0.276	-0.285
	[10.187]	[10.304]	[7.093]	[7.997]	[-0.803]	[-1.123]
Firm experience * Post-sanction	0.116***	0.092***	3.985***	3.637***	-1.209***	-0.285
	[7.471]	[7.933]	[7.093]	[7.997]	[-3.198]	[-1.123]
Bank experience (# loans)	0.021***	0.019***	-0.264***	-0.282***	-0.004	-0.920***
	[5.480]	[6.179]	[-5.094]	[-4.852]	[-0.029]	[-2.987]
Bank experience * Post-sanction	0.027***	0.023***	-0.091*	0.032	-1.077**	-0.920***
	[5.853]	[7.000]	[-1.687]	[1.173]	[-2.365]	[-2.987]
Loan controls	Y	Y	Y	Y	Y	Y
Firm controls	Y	Y	Y	Y	Y	Y
Post-sanction variable	N	Y	N	Y	N	Y
Observations	27,337	25,330	27,337	25,330	5,237	5,776
R-squarred	0.558	0.603	0.691	0.679	0.798	0.773
F-test	143.3	610.7	88.35	372.7	477	312.6
Year FE	N	Y		Y		Y
Industry(SIC3)*Year FE	Y		Y		Y	
Bank*Year 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). We estimate the regression:

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

where b, s, f, t refer to bank, sector, firm and year, respectively. We estimate this regression on a loan-level sample originated from 1999 to 2011. All variables are defined in Table 1. All specifications include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. Standard errors are robust and clustered at the bank level. The *,**,*** marks denote the statistical significance at the 10, 5, and 1% level, respectively.

Table 11: Alternative specifications

	I	II	III	IV	V	VI	VII	VIII	IX
	Repeated syndicate member			Exclude NBER recessions			Exclude TOP3 banks		
Dependent variable	Prob(lead)	Lender shares (%)	Lead lender shares (%)	Prob(lead)	Lender shares (%)	Lead lender shares (%)	Prob(lead)	Lender shares (%)	Lead lender shares (%)
Sectoral experience (SIC2)	0.125**	10.970***	39.278*	0.197***	15.699***	21.601***	0.160***	13.700***	18.591**
	[2.028]	[5.751]	[1.951]	[8.219]	[10.730]	[4.642]	[5.209]	[6.521]	[2.450]
Firm experience (# loans)	0.174***	0.930***	0.882*	0.157***	1.855***	-1.016***	0.180***	3.262***	-1.523***
	[26.033]	[6.601]	[1.937]	[19.144]	[12.471]	[-6.204]	[18.455]	[8.091]	[-5.993]
Bank experience (# loans)	0.019***	0.067*	0.003	0.018***	-0.186***	-0.827***	0.024***	-0.250***	-1.684***
	[11.796]	[1.860]	[0.023]	[19.448]	[-7.829]	[-10.532]	[6.394]	[-4.105]	[-7.209]
Loan controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	10,751	10,751	1,080	52,852	52,852	13,876	45,678	45,678	7,909
R-squarred	0.553	0.690	0.764	0.490	0.600	0.709	0.534	0.647	0.754
F-test	89.55	71.03	8.084	292	461.8	199.1	103.7	77	179.3
Bank*Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry(SIC3)*Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Clustered standard errors	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

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

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

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

Table 12: Experience and market shares

	I	II	III
Dependent variable	Prob(lead)	Lender shares (%)	Lead Lender shares (%)
Sectoral experience (SIC2)	0.187***	15.397***	23.829***
	[8.232]	[10.625]	[5.033]
Firm experience (# loans)	0.157***	1.820***	-1.024***
	[20.753]	[12.975]	[-6.535]
Bank experience (# loans)	0.018***	-0.181***	-0.737***
	[18.528]	[-7.693]	[-9.069]
Sectoral shares (SIC2)	0.038**	3.396***	1.652
	[2.434]	[4.504]	[0.409]
Loan controls	Y	Y	Y
Firm controls	Y	Y	Y
Observations	60,148	60,148	16,101
Adjusted R-squared	0.426	0.550	0.605
F-test	278.2	446.7	195.6
Bank*Year FE	Y	Y	Y
Industry*Year FE	Y	Y	Y
Clustered standard errors	Bank	Bank	Bank

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

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

where b, s, f, t refer to bank, sector, firm and year, respectively. We estimate this regression on a loan-level sample originated from 1987 to 2014. All variables are defined in Table 1. All specifications include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. 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 13: The impact of experience on firm's outcomes after the loan origination

	I	II	III	IV
Dependent variable	$Size_{t+1}$	$Sales_{t+1}$	ROA_{t+1}	$Dividend_{t+1}$
Sectoral experience (SIC2)	0.992***	0.789***	0.034**	0.062**
	[10.337]	[7.822]	[2.344]	[2.459]
Firm experience (# loans)	-0.035***	-0.030***	0.001	-0.008***
	[-4.725]	[-4.089]	[1.221]	[-3.679]
Bank experience (# loans)	0.006***	0.006***	0.001**	0.001**
	[3.640]	[3.231]	[2.466]	[2.133]
Lagged dependent variable	Y	Y	Y	Y
Loan controls	Y	Y	Y	Y
Observations	60,148	60,148	60,148	60,148
Adjusted R-squared	0.550	0.547	0.246	0.396
F-test	111.3	101.8	19.66	65.98
Bank*Year FE	Y	Y	Y	Y
Industry*Year FE	Y	Y	Y	Y
Clustered standard errors	Firm	Firm	Firm	Firm

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

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

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

Appendix

Table A1: Aggregate lending in the commercial market and enforcement actions

	I	II
Dependent variable:	Total loans	Total loans
Enforcement	-0.044***	-0.030***
	[-6.742]	[-4.070]
Deposits		0.276***
		[2.942]
Tier1		-0.267***
		[-3.024]
NPLs		-0.985**
		[-2.453]
HHI-deposits		3.687**
		[2.551]
Observations	30,857	26,444
Adjusted R-squared	0.844	0.903
F-test	45.46	18.46
Year FE	Y	Y
Bank FE	Y	Y
Clustered standard errors	Bank	Bank

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

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

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

Table A2: Sensitivity test for SIC sectors

	I	II	III	IV	V	VI	VII	VIII	IX
Dependent variable:		Prob(lead)			Lender shares (%)			Lead lender shares (%)	
Sectoral experience (SIC1)	0.098***			7.121***			9.163***		
	[3.959]			[4.933]			[2.771]		
Sectoral experience (SIC3)		0.222***			19.499***			29.504***	
		[5.741]			[8.688]			[4.053]	
Sectoral experience (SIC4)			0.220***			19.800***			34.532***
			[5.326]			[8.204]			[4.880]
Firm experience (# loans)	0.157***	0.156***	0.156***	1.827***	1.816***	1.815***	-1.025***	-1.019***	-1.018***
	[17.933]	[17.871]	[17.874]	[4.919]	[4.912]	[4.920]	[-6.064]	[-5.941]	[-5.944]
Bank experience (# loans)	0.018***	0.018***	0.018***	-0.182***	-0.182***	-0.181***	-0.738**	-0.736**	-0.734**
	[4.572]	[4.584]	[4.584]	[-5.603]	[-5.604]	[-5.602]	[-2.484]	[-2.478]	[-2.471]
Loan controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	60,148	60,148	60,148	60,148	60,148	60,148	16,101	16,101	16,101
R-squarred	0.489	0.489	0.489	0.598	0.599	0.599	0.702	0.703	0.704
F-test	157.7	153	154	102.2	93.21	93.13	138	145.3	148.4
Industry*Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank*Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Clustered standard errors	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

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

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

where b, s, f, t refer to bank, sector, firm and year, respectively. We estimate this regression on a loan-level sample originated from 1987 to 2014. All variables are defined in Table 1. All specifications include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. 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 A3: Experience and non-linearities

	I	II	III	IV	V	VI
Dependent variable:	Prob(lead)		Lender shares (%)		Cond. ender shares (%)	
Sectoral experience (SIC2)	0.561***	0.330***	38.871***	34.871***	51.966***	65.716***
	[7.584]	[5.392]	[8.329]	[7.322]	[4.354]	[5.758]
Sectoral experience (SIC2)^2	-0.594***	-0.263***	-37.151***	-28.406***	-46.848***	-53.928***
	[-6.820]	[-4.364]	[-6.753]	[-5.822]	[-3.078]	[-4.481]
Firm experience (# loans)	0.231***	0.198***	2.813***	2.462***	-1.632***	-0.757***
	[16.837]	[16.928]	[4.459]	[4.600]	[-6.556]	[-6.049]
Firm experience (# loans)^2	-0.010***	-0.008***	-0.124***	-0.120***	0.078**	0.027
	[-4.791]	[-4.043]	[-2.768]	[-3.125]	[2.467]	[1.359]
Bank experience (# loans)	0.035***	0.029***	-0.490***	-0.620***	-2.458***	-2.038***
	[6.262]	[6.394]	[-5.242]	[-7.974]	[-4.382]	[-4.566]
Bank experience (# loans)^2	-0.001***	-0.000***	0.009***	0.012***	0.043***	0.035***
	[-4.002]	[-4.022]	[4.991]	[6.396]	[3.657]	[3.566]
Loan controls	Y	Y	Y	Y	Y	Y
Firm controls	Y	Y	Y	Y	Y	Y
Observations	60,148	56,060	60,148	56,060	16,101	16,144
R-squarred	0.519	0.560	0.602	0.589	0.713	0.689
F-test	415.1	594.7	86.15	99.23	194.3	403
Year FE	N	Y	N	Y	N	Y
Bank*Year FE	Y	N	Y	N	Y	N
Industry (SIC3)*Year FE	Y	N	Y	N	Y	N
Bank*Industry (SIC3) FE	N	Y	N	Y	N	Y
Clustered standard errors	Bank	Bank	Bank	Bank	Bank	Bank

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

$$Y_{b,f,t} = \alpha' + \lambda_1 Sector^{Exper}_{b,s,t} + \lambda_2 Firm^{Exper}_{b,f,t} + \lambda_3 Bank^{Exper}_{b,t} + \lambda_4 X^2_{b,t} + \beta_1 L_{b,t-1} + \beta_2 F_{f,t-1} + \epsilon_{b,f,t}$$

where b refers to bank; f for firm; and t for years. 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.