Bank Specialization and the Design of Loan Contracts

Marco Giometti[†] and Stefano Pietrosanti[‡]

[†]The Wharton School, University of Pennsylvania

[‡]Department of Economics, University of Pennsylvania

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Abstract. Using data on the US syndicated loan market, we show that banks specialize in lending towards specific industrial sectors. Specialization is persistent over time and common across industries. This contrasts naive interpretations of classical theories of financial intermediation built upon portfolio diversification. Using detailed information on credit agreements, we show that the typical loan contract between a bank specialized in an industry and a firm in the same industry has less restrictive covenants and lower spreads. This, with respect to a loan arranged by the same bank, at the same time, to a firm in another industry in which the bank is not specialized in. This result cannot be fully explained by relationship lending, high propensity to internalize spillovers from credit decisions within an industry, or geographical proximity. Interpreting our findings in light of the information theory of covenants, we suggest that the lending advantage associated with bank specialization is likely to stem from an information advantage in screening and monitoring.

Keywords: Bank organization, Security design, Covenant, Monitoring, Screening.

JEL Classification: L15, L22, G21, G30, G32.

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1. Introduction

Diversification of risk plays a central role in many theories of financial intermediation (e.g. Boyd and Prescott, 1986; Diamond, 1984). However, empirical evidence shows that banks often concentrate their lending across multiple dimensions, including geography, scale, and industry.[1] There has been extensive work showing how portfolio concentration can have important implications for banks' economic performance and risk, as well as for their borrowers via the transmission of shocks through the banking sector.[2]

What is less well understood are the implications of bank specialization for security design. In particular, there is no or little evidence on the role of specialization in lending on loan contract terms, such as covenants or loan spreads.[3] We believe it is important to fill this gap for two reasons. First, contracts, by construction, specify the allocation of resources and the division of surplus, both of which affect welfare. Second, they reflect the preferences of the contracting parties, and as such, they provide insight into the objectives of those parties. They might inform a better understanding of the lending advantages associated to bank specialization, and ultimately of how the structure of credit markets interacts with financial contracting.

The goal of this paper is to address the question of how specialization in bank lending affects the design of loan contracts, in the context of the $2 trillion, corporate syndicated loan market.[4] First, we document that the average bank's loan portfolio has a higher industry concentration than the market, that bank specialization is common across industries and that it is persistent over time. Then, we show that loan contracts display less restrictive covenants when the borrower belongs to an industry in which the bank is specialized, with no higher spreads or fees. We interpret this finding in the light of the theory of covenant strictness as a proxy for the degree of information frictions between borrowers and lenders (Garleanu and Zwiebel, 2008), supporting an explanation of bank specialization based on information advantages in screening and monitoring a specific type of projects.

1. Hughes et al. (1996); Carey et al. (1998); Berger and Robert (2001); Paravisini et al. (2018).
2. On the relation between bank portfolio concentration and related performances, see Acharya et al. (2006); Beck et al. (2018); Boeve et al. (2010); Hayden et al. (2007); Tabak et al. (2011). On the real effects of bank specialization, see Schwert (2018); Paravisini et al. (2018); De Jonghe et al. (2019).
3. One exception is represented by the study of Daniels and Ramirez (2008), in which they document that banks specialize in lending towards large firms and non banks towards small firms, with banks demanding lower spreads.
4. U.S. syndicated lending topples records in 2017, Reuters, December 2017.

In order to perform our analysis, we obtain data on syndicated loans from LPC DealScan, and we merge it with Compustat. The resulting dataset is a loan-level panel with bank, firm and loan characteristics, from 1996 to 2016.[5] We use this data to estimate the degree of diversification of bank loan portfolios. We then analyze the extent to which banks specialize their lending towards different sectors adapting the approach in Paravisini et al. (2018) to our setting. A bank is defined as specialized in a sector if it has an abnormally large portfolio share of loans towards a sector, relative to other banks. Intuitively, this measure captures the extent to which corporate lending on banks' balance sheets deviates from a value-weighted portfolio. In doing so, the measure accounts for heterogeneity in the size of sectors in the economy and in the size of bank sectoral lending relative to the bank's overall corporate lending.

We find clear evidence of bank specialization. First, we show that the average bank displays more concentration in lending than what would be implied by the overall distribution of credit in the market. Second, we document that certain banks specialize in lending by holding a disproportionately large share of loans in certain sectors. In particular, each sector consistently displays at least one specialized bank. This specialization is persistent: a bank that is specialized in a given year has a 20% probability of being specialized 10 years after.

We then explore the implications of bank specialization for the design of loan contracts. In particular, we focus on the allocation of control rights and cash flow rights between the lender and the borrower. To proxy for the degree of ex-ante control rights allocated to the lender, we employ the measure of contract strictness developed by Demerjian and Owens (2016).[6] Intuitively, this measure captures the ex-ante probability of violating at least one of the covenants embedded in the contract. For cash flow rights, we use loan spreads, i.e. the all-in-drawn spread and the all-in-undrawn spread.[7] Looking at both is important as these contract terms are jointly determined, and there might be a trade-off between them (Bradley and Roberts, 2015).

We find that the average loan contract between a bank specialized in a sector and a borrower

5. We choose this sample period for two reasons. First, coverage of the syndicated loan market sharply improves in DealScan after 1995 (Chava and Roberts, 2008). Second, in our main analysis we use the text-based network industry classification developed by Hoberg and Phillips (2010, 2016), which is available starting from 1996.
6. This measure is the non-parametric version of the one originally developed by Murfin (2012).
7. The former is a fee paid over the base rate (usually LIBOR) for each dollar of credit drawn, whereas the latter is a fee for each dollar of credit committed, but undrawn.

from that sector includes covenants that are 7 percentage points less restrictive, and an all-in-drawn spread that is 20 basis points lower. This, with respect to a loan contract granted by the same bank, in the same year, to a firm in another sector. The observed effects are economically and statistically significant. For contract strictness it amounts to 17% of the empirical standard deviation; for the spread, it amounts to 15% of the empirical standard deviation.

Comparing loans made by the same bank in the same year rules out that our finding is driven by unobserved, time-varying lender heterogeneity. However, the observed variation in contract might be simply driven by specialized banks matching systematically with different firms. We take several steps to mitigate this concern. First, we control for observable proxies of borrower risk, such as distance to default, leverage, liquidity and ability to provide collateral. Second, we restrict our analysis to firms that borrow from more than one bank over the duration of our sample, employing a within-firm approach. Third, we restrict our comparison to loans made to firms that have the same credit rating. The main finding does not change: the average loan contract between a bank specialized in a sector and a borrower from that sector includes a covenant structure that is less restrictive, and it does not display higher spreads.

We then ask whether our findings can improve our understanding of the lending advantages associated with bank specialization. Theory suggests that the degree of allocation of ex-ante control rights to the lender should be directly proportional to the level of asymmetric information that exists between a borrower and a lender over potential future transfers from debt to equity (Garleanu and Zwiebel, 2008). In this view, the strictness of the covenant structure embedded in a loan contract captures the information distance between a borrower and a lender. Therefore, a plausible interpretation of our results implies the existence of an *industry-specific* information advantage for banks specializing their lending towards a specific industry. The fact that a less restrictive covenant structure is not compensated by higher spreads provides further support to this interpretation.

We rule out a number of alternative explanations for our findings. First, we show that specialization in lending toward an industry does not simply reflect a pattern of relationship lending with borrowers in that industry. While it is indeed true that the longer the relationship with a given borrower the less restrictive the loan contract – consistently with the work of Prilmeier (2017) – this appears to be uncorrelated with bank specialization. Second, our results are not driven by geographical specialization, which confirms the notion of an industry-specific information advantage. This is consistent with the recent evidence provided by Di and Pattison (2019) for small business loans. Third, specialized banks might have high market share in an industry. Recent work by Giannetti and Saidi (2018) suggest that lenders with high market shares in an industry have a high propensity to internalize the spillovers of their credit decision. This might involve writing less strict contracts to avoid triggering potentially costly defaults or renegotiations, and could represent a different economic mechanism that would explain our results.[8] We show that this is not the case, and find that banks with high market shares actually write stricter contracts, possibly implying a higher bargaining power in the contracting process.

Finally, to further validate our interpretation, we use defaults on lenders' loan portfolios as a plausible source of exogenous variation in lenders' perception of their own screening ability (Murfin, 2012). We look at the extent to which default of firms in each bank's loan portfolio affects the terms (covenant strictness and cost of credit) of the new contracts each bank underwrites. We show that a bank is more sensitive to the default of a firm whenever such firm belongs to a sector in which the bank is specialized, as it is expected under an interpretation of specialization patterns as stemming from information advantage.

Related Literature. With this paper, we contribute to and connect two different strands of literature. First, to the literature focusing on patterns of specialization in the market for credit, and their effects. For example, Carey et al. (1998); Daniels and Ramirez (2008) highlight how different types of financial intermediaries – such as banks and private finance companies – specialize in lending towards different types of firms. Acharya et al. (2006); Tabak et al. (2011); Beck et al. (2018), document how bank concentration either does not have negative effects on bank risk, or decreases it. Finally, Paravisini et al. (2018) and De Jonghe et al. (2019) show that even within a single class of intermediaries – banks – there is specialization in lending towards specific firms, and this drives the effect of bank shocks on firms.

Among these works, the closest one is Paravisini et al. (2018). Paravisini et al. (2018) introduces the measure of specialization we also use in our paper, and applies it to the context of

8. There is a large literature documenting negative consequences of debt covenant violations on investment, employment, and other firm-level outcomes. See Chava and Roberts (2008); Chodorow-Reich (2013).

the market for credit to Peruvian exporters. Using that measure, it provides a test of information advantage based on the degree of substitutability between credit by specialized and non-specialized lenders. We contribute in two ways. First, to the best of our knowledge, we are the first to look at bank specialization in the context of security design. We show that specialization is an important determinant of contract features. In this way we provide an alternative test to identify the presence of information advantage in lending by specialized banks, based on information distance between borrowers and lenders. Second, we show that specialization is present in a market for large corporate loans.

Furthermore, our finding regarding the importance of bank specialization for contract features contributes to the study of financial contracting and its determinants. Several works highlight the role of borrower or lender characteristics for the determination of loan covenants (e.g. Berlin and Mester, 1992; Billett et al., 2007; Demiroglu and James, 2010; Murfin, 2012; Bradley and Roberts, 2015), or pricing (e.g. Ivashina, 2009; Cai et al., 2018). Our results stress, instead, the importance of taking into account borrowers and lenders characteristics *jointly* when looking at the determinants of contracts' features. In this sense, we are close to Bao (2019), who studies how peer effects in loan portfolios affect the cost of credit. With respect to her study, we focus more broadly on security design.

The paper proceeds as follows. In Section 2 we describe the sample construction, discuss how we measure specialization, and provide evidence on bank specialization in the syndicated loan market. In Section 3 we present our empirical strategy, our findings, and discuss several alternative explanations. In Section 4 we provide concluding remarks.

2. Data and Measurement

To characterize specialization and to study its implications, we construct a sample of syndicated loans matched with bank and firm characteristics. Below we describe the sample construction, introduce and discuss the way we measure bank specialization, present the other economic variables we employ in our analysis, and summarize the sample characteristics.

2.1. Sample Construction

Our two main sources of data for this paper are LPC DealScan and Compustat. LPC DealScan contains detailed information on syndicated loans, including loan amounts, covenants, pricing, and maturity. Compustat provides balance-sheet information for both banks and firms. We merge the loan data with borrower characteristics thanks to the linking table provided by Chava and Roberts (2008), which matches firms in Compustat to borrowers in DealScan from 1987 to 2017.[9] We also merge firm characteristics in Compustat with the industry classification developed by Hoberg and Phillips (2010, 2016), which is available for most public companies present in Compustat. We obtain information on banks by matching lenders in DealScan with bank characteristics, thanks to the linking table provided by Schwert (2018), which identifies the Bank Holding Company (BHC) of all DealScan lenders with at least 50 loans, or $10 billion loan volume in the matched DealScan-Compustat sample. Following the literature we drop all loans to financial corporations (SIC codes from 6000 to 6999). The final matched dataset contains 66% of DealScan-Compustat loan volume, and accounts for mergers (Schwert, 2018). We attribute loans of the merged bank to the new entity from the time of the merge onward.

In this paper, we define a bank to be the BHC, not the individual DealScan lender. As most loans in DealScan are syndicated, the same loans will be associated to one or more lead arrangers, and several other participants bank. Consistently with other studies, we focus only on the lead arranger(s), and we attribute the whole loan amount to the lead arranger(s)of the syndicate.[10] This choice stems from observing that a lead arranger is the bank in charge of the active management of the loan, even if it does not retain the entirety of its amount on their balance sheets (Ivashina, 2009). If there are multiple lead arrangers, we split the loan amount equally among them. We identify a lead arranger following the procedure outlined in Chakraborty et al. (2018), and we drop those loans that appear to have more than 10 lead arrangers, as those are probably the result of an incorrect classification.[11]

9. The linking table is constantly being updated, as of November 2018 this is the most recent and comprehensive version.

10. See, for example, Schwert (2018); Prilmeier (2017); Chakraborty et al. (2018).

11. Specifically, DealScan has two fields that can be used to determine the lead arranger, a text variable that defines the lender role in the syndicate and a yes/no lead arranger credit variable. As Chakraborty et al. (2018), who in turn follow Bharath et al. (2009), we define the following hierarchy: 1) lender is denoted as "Admin Agent", 2) lender is denoted as "Lead bank", 3) lender is denoted as "Lead arranger", 4) lender is denoted as "Mandated

The unit of observation in DealScan is a loan facility. However, information on loan covenants is available only at the package level. Since in our analysis the main dependent variable is contract strictness, which is based on covenants, we conduct our analysis at the package level, aggregating facility-level information by weighting the facility characteristics – such as the spreads and maturity – by the respective facility amounts. Therefore the observation level in the dataset is the package-bank-firm triplet at a quarterly frequency. Following Murfin (2012), we also report the contracting date of a package as 90 days prior to the DealScan reported start date, to account for the time lag between the effective moment in which banks and firms commit to loan contract terms and the legal start date reported by DealScan.

2.2. Two Measures of Bank Specialization

2.2.1. Methodology

We are interested in understanding whether banks specialize by lending towards specific sectors of the economy. To address this issue, we employ two approaches. The first consists in comparing how diversified the commercial lending portfolio of an average bank is relative to the whole syndicated-loan market portfolio. Intuitively, if banks are less diversified than the market, it means at the very least that they prefer to concentrate their lending towards some, but not all, sectors of the economy – implying a certain degree of specialization. The second involves identifying those banks that are abnormally exposed to a given industrial sector with respect to the other banks active in that sector. This second approach adapts the measure developed by Paravisini et al. (2018).

In the first approach, we employ the *entropy* metric, originally employed in the social sciences to measure the degree of diversity in a population of individuals.[12] We employ this measure to the context of banking, and we use it to characterize the level of diversification of the market

lead arranger", 5) lender is denoted as "Mandated arranger", 6) lender is denoted as either "Arranger" or "Agent" and has a "yes" for the lead arranger credit, 7) lender is denoted as either "Arrange" or "Agent" and has a "no" for the lead arranger credit, 8) lender has a "yes" for the lead arranger credit but has a role other than those previously listed ("Participant" and "Secondary investor" are also excluded), 9) lender has a "no" for the lead arranger credit but has a role other than those previously listed ("Participant" and "Secondary investor" are also excluded), and 10) lender is denoted as a "Participant" or "Secondary investor". For a given loan package, the lender with the highest title (following our ten-part hierarchy) is considered the lead arranger.

12. It has been used extensively in studies on segregation and inequality. See White (1986) for a discussion.

portfolio, and that of the average bank, with respect to the different industries in the economy.[13] For a given bank, the entropy of its commercial lending portfolio is defined as follows:

$$E_t^b = -\sum_{i=1}^{I} L_{it}^b \log\left(L_{it}^b\right) \tag{1}$$

in which L_{it}^b denotes the portfolio share of loans from bank b, towards industry i in the list of industries from 1 to I, at time t. E_t^b reaches its maximum – which is equal to $\log(I)$ – in presence of a perfectly diversified portfolio, i.e. $L_{it}^b = 1/I \ \forall i \in I$, whereas we can impose its minimum to be zero in case of no diversification, i.e. $L_{it}^b = 1$ for only one industry i, and 0 for all the others.

We can then compute the entropy of the average bank by simply taking a weighted average of the entropy of all banks, in which the weights are represented by a bank's share of total credit:

$$\bar{E}_t^b = \sum_{b=1}^{B} \frac{L_t^b}{L_t} \left(-\sum_{i=1}^{I} L_{it}^b \log\left(L_{it}^b\right)\right) \tag{2}$$

in which $L_t^b = \sum_{i=1}^{I} L_{it}^b$ is the amount of credit – to any industry – issued by bank b and still outstanding at time t, and $L_t = \sum_{b=1}^{B} L_t^b$ is the total amount of credit outstanding at time t.

Similarly, we can define the entropy for the market portfolio. If we think of all the credit exposures of all the banks, summed together at a given time, as the "market" portfolio for the syndicated loan market at that time, we can define the entropy of the "market" portfolio as follows:

$$E_t^M = -\sum_{i=1}^{I} L_{it} \log\left(L_{it}\right) \tag{3}$$

in which $L_{it} = \sum_{b=1}^{B} L_{it}^b$ denotes the share of credit – from all banks – towards industry i, in the whole syndicated loan market.

In the second approach, we adapt the methodology developed by Paravisini et al. (2018) to capture bank specialization at the industry level. According to this approach, a bank is specialized in lending towards a given industry if its portfolio share of loans outstanding in that industry is abnormally large, *relative to other banks*. More formally, specialization is a dummy

13. An alternative could be to use the HHI index, but we prefer the entropy as it is a measure of diversification, whereas HHI is a measure of concentration. See Avila et al. (2013) for a comparison of these different approaches to measuring portfolio concentration/diversification.

variable, defined as follows:

$$Spec^b_{it} = \begin{cases} 1 & \text{if } L^b_{it} \geq L^*_{it} \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

in which L^b_{it} is, as above, the share of credit issued bank b to industry i outstanding at time t, and L^*_{it} is an extreme value defined as the sum of the 75^{th} percentile of the distribution of bank portfolio shares in industry i at time t and 1.5 the inter-quartile range of the same distribution. In other words, according to this approach, a bank is specialized in an industry if it is a right-tail outlier in the distribution of portfolio shares of lending by all banks towards that industry.

To help understand this approach and highlight its advantages, Figure 1 presents some simple examples involving two banks and an economy with only wo sectors. In panel (a) neither bank is specialized as each bank's balance sheet is split in half between the two sectors, and the pattern is equal across banks. Panel (c) is similar to the first case. Although one bank is larger and the other smaller, and they are both mostly exposed to sector A, the pattern of exposure is the same. Thus, large exposures to sector A might simply reflect a different demand of credit from sector A with respect to sector B in that particular economy, and we cannot detect evidence that one particular bank is specialized.

In panel (b), instead, we have an example of specialization. In this case, Bank 1 is specialized in sector A and Bank 2 in sector B. Each bank could both lend to both sectors – and they do – but each of them is abnormally exposed to one sector, indicating a bank-level pattern that is coherent with comparative advantage in lending towards that sector. This does not depend simply from the amount of credit that goes from each bank to each sector. In fact, in panel (d), in which Bank 1 is specialized in sector A only, and bank B is specialized in sector B: while Bank 1 provides overall more credit to sector B than Bank 2, its portfolio share is really small compared to Bank 2, which has all of its loan portfolio invested in sector B.

2.2.2. Specialization in Lending in the US Syndicated Loan Market

To compute these measures of specialization, we need granular information on banks' commercial lending portfolio. For US banks there is no balance-sheet information at the level of granularity required – i.e. with a breakdown by industrial sector. Therefore, we rely on

DealScan and focus on syndicated lending, which nonetheless represents a sizable portion of the corporate loan market in the US. This allows us to obtain data on bank-firm credit relationships. However, DealScan only provides information on loan originations.

Similarly to Chakraborty et al. (2018) and Lin and Paravisini (2012), we create a panel that resembles a credit registry by aggregating DealScan loan-level data at the bank-firm relationship level over time. We assume each loan is outstanding until the original end date, or, if the information is available on DealScan, until the amended end date.[14] In this way we obtain a dynamic representation of the commercial lending portfolio for each bank in our sample, which we then use to compute time-varying portfolio shares in each industry by aggregating loan amounts for each bank-firm relationship at each given point in time.

Since a bank portfolio share towards a given industry is a proxy to capture a comparative advantage in lending towards specific types of project in the economy, we use the Text-based Network Industry Classification (TNIC) developed by Hoberg and Phillips (2010, 2016), which better measures similarities across firms with respect to a standard SIC or NAICS classification, and is updated annually.

We employ the 25-industry version of their classification, as this ensures a good balance between the number of firms present in DealScan in each industry and a sufficient precision in the characterization of the different set of projects in the economy. We apply the methodology described in the previous subsection, and compute the two measures of specialization for all the banks in the sample of syndicated loans granted to firms that have a TNIC classification, from 1996 to 2016.

First, we look at the measure of loan portfolio diversification. In Figure 2, we plot the entropy of the commercial lending portfolio for the average bank computed for each quarter as in Equation (2), and the same measure computed for the market portfolio as in Equation (3). Given that a larger value of this measure imply larger diversification, a comparison of the two reveals that the loan portfolio of the average bank is *less* diversified than the market. Comparing the average entropy of the market portfolio(~ 2.8) and that of the average bank (~ 2.5) over

14. It is possible that a loan is renegotiated and appears as a new loan in DealScan, and this might be potentially problematic for us if loan renegotiation is not identically and in dependently distributed. To partially address this issue, we drop of our sample all the loans that have a description such as "This loans amends and restates..." in the various "comment" fields available in Dealscan.

time, we see that the average bank is about 10% less diversified than the market. This implies that not every bank is lending to every industry in the same way, providing suggestive evidence of specialization in lending.

Second, we look at specialization by industry. In Table 1 we report the summary statistics for the distribution of bank lending shares for each industry i, L_{it}^{b}, demeaned by the average share of across all banks in that industry, $\bar{L}_{it}$. From this table we can infer that the within-industry distribution of $L_{it}^{b} - \bar{L}_{it}$ is right-skewed, since the median is negative for all industries and the skewness is large and positive for every country. This implies that each industry will have at least one bank specialized in lending towards that industry.

Figure 3 displays the box-and-whisker plot of the within-country distribution of the demeaned bank lending shares for each industry at four different moment in time, and visually corroborates the evidence in Table 1. Specialization in lending is common across time and industry. Moreover, specialization is persistent over time; Figure 4 plots the autocorrelation of $Spec_{it}^{b}$ defined in Equation (4), and we can see that a bank specialized in lending towards a an industry in a given year is 20% more likely to be specialized in lending towards the same industry 10 years later, with respect to a bank that was not specialized. Overall, the evidence presented in this section points to lenders' specialization in lending as a defining feature of the US syndicated loan market.

2.3. Measurement of Economic Variables

Dependent Variables: Loan Contract Strictness and Loan Spreads

Our ultimate goal is to understand whether specialization is associated to information advantages in lending towards specific sectors of the economy. We therefore need an empirical proxy to capture the notion of information advantage when a bank is lending to firms in a given industry.

To achieve this, we build upon the theoretical work by Garleanu and Zwiebel (2008), and consider the covenant structure embedded in a loan contract as capturing the information "distance" between a bank and a firm. The more restrictive the contract – in terms of what the firm can or cannot do in order not to trigger a technical default by violating a covenant – the less information a bank has about a borrower, according to the theory. However, in presence of multiple covenants it is not obvious how to assess the overall strictness of the loan contract. Therefore, we are going to rely on the measure of contract strictness developed and made available by Demerjian and Owens (2016), which improves on the original measure proposed by Murfin (2012).[15]

Contract strictness is defined as the *ex-ante* probability of violating at least one *financial* covenant during the life-time of the loan, ranging from 0 to 100. This measure is characterized by four properties, all valid on an "all else equal" basis. First, it increases in the number of covenants; second, for a fixed number of covenants, it decreases in the initial slack of a covenant, defined as the distance between the level of the covenant threshold and the starting level of the corresponding financial ratio; third, it increases in the volatility of the ratios targeted by covenants; fourth, it decreases in the correlation between covenants—intuitively, since a technical default is triggered even if a single covenant is violated, contracting on independent financial ratios increases the probability of violating at least one.

In order to draw conclusions it is also important to track the cost of credit. Covenant and the pricing structure of a loan are often jointly determined, with a potential trade-off between them—stricter contracts might be associated with lower costs and viceversa. Therefore we also collect information on loan pricing available on DealScan, specifically the All-in Drawn Spread (AISD) and the All-in Undrawn Spread (AIUD). The AISD is the sum of the spread over the base rate, generally LIBOR that a borrower need to pay for every dollar of credit drawn down and all the annual fees paid to the lender. The AIUD is the annual cost that a borrower is charged by the lender on the portion of credit that is not drawn down.

Bank, Firm, and Relationship level Variables

We obtain bank- and firm-level variables from Compustat, and information on loan quantities and characteristics from Dealscan. From this merged dataset, we construct proxies for relationship lending and banks' market share.

First, following Prilmeier (2017), we create a measure of *Relationship Intensity* and a measure of *Relationship Length*. $Rel.\ Intensity_{f,b,t}$ is defined at time t as the fraction of credit firm f has

15. It can be downloaded at http://faculty.washington.edu/pdemerj/data.html.

obtained from bank b over the total amount of credit firm f has received over the previous 60 quarters (5 years). *Rel. Length*$_{f,b,t}$ is defined as the time elapsed between period t and the first interaction of firm f and bank b in DealScan. Then, we collect information on the geographic distance between the borrower and the lender, to proxy for "arms-length" credit relationships. We use historical data on firm and bank locations available on Compustat to construct a dummy variable, *Same State*$_{f,b,t}$. This dummy equals to 1 if bank b and firm f are in the same state at time t, and 0 otherwise.

Finally, we compute each bank *Market Share*$_{b,f,t}$. This is the fraction of credit that a bank b provides to the industry of firm f over the total credit that industry receives at period $t-1$. Taking bank market share into account is important. For example, Giannetti and Saidi (2018) shows that banks with a large market share in an industry are more likely to internalize the systemic consequences of credit supply contractions on that industry.

2.4. Sample Characteristics

Table 2 reports summary statistics for the samples we use in our empirical analysis. In particular, we distinguish two samples. The first one, "Matched Sample" is the full DealScan-Compustat matched sample , constructed as described in Section 2.1. The second one, "Strictness Sample" is a subsample obtained from merging the Matched Sample with data on the measure of contract strictness developed by Demerjian and Owens (2016), and represents the sample employed in our main empirical analyses.

The top panel of Table 2 reports information on the characteristics of loan-level variables in our samples. The Strictness Sample includes $11,223$ distinct loans. On average, a loan agreement contains two financial covenants, displays a level of strictness such that the borrower has 36% probability to violate at least one of the covenants, and contains an All-In-Drawn Spread of 188 basis points, with relatively small average fees—the mean All-In-Undrawn Spread is 26 basis points. The same average loan has maturity of approximately 45 months, amounts to approx. $500 million and the average number of members in the syndicate is 9. These statistics are similar in the larger Matched sample, which displays a smaller number of covenants, larger average loan amount, and a slightly smaller number of syndicate members.

The mid panel of Table 2 reports information on the borrowers in our samples. The Strictness

Sample includes 10,721 firm-quarter observations for 3,673 firms. These are large firms – with on average $1 billion in total assets – having higher leverage and profitability than the average firm in Compustat. About 50% do not have a long-term issuer credit rating, and for those that have a rating, the average rating is BBB-/BB+.[16] Over our sample period (1996-2016), they enter, on average, into 10 syndicated loan agreements and interact with a relatively small number of lenders, approx. 4. With the exception of book leverage, which is quite noisy, these statistics are coherent in both the Strictness Sample and the Matched Sample.

Finally, the bottom panel of Table 2 reports information on the lenders in our samples. The Strictness Sample includes 2,155 bank-quarter observations for 89 banks. The average bank is large, with $169 billion in total assets, with approx. 700 loans arranged over our sample period.

3. Bank Specialization and Loan Contract Terms

In this section we explore the effect of bank specialization in lending on loan contract strictness and the cost of credit. We first perform a simple univariate analysis, which highlights potential non-randomness in the matching between banks and firms, and underscores to the need of a more sophisticated regression framework. Employing different multivariate specifications aimed at mitigating these concerns, we then show that bank specialization is associated with significantly lower contract strictness, and no higher spreads.

We interpret this evidence as support for explanations of bank specialization based on lending advantages, and we suggest that part of this advantage is an information advantage, which is sector-specific. Finally, using default on lenders' loan portfolios as a possible source of exogenous variation in banks' perception of their expertise in dealing with a certain industrial sector, we show that specialized banks are more sensitive to defaults of firms in their sector of specialization and less sensitive to default to other firms, providing further evidence in line with this interpretation.

16. Rating is a categorical variable. We assign value 1 to AAA ratings, 2 to AA+, and so on. The largest value is 20, assigned to "D" or "SD" indicating default in the S&P Long Term Credit Rating.

3.1. Univariate Analysis

We begin by comparing the characteristics of loans arranged by a bank specialized in lending towards the industry a given borrower belongs to, with all other loans. To make things clear, a loan to a firm f starting at time t is considered to be arranged by a specialized bank b if $Spec^{b}_{i,t-1}$, defined in Equation (4), is equal to 1 and the firm f belongs to industry i. The top panel of Table 3 reports the results of these basic univariate t-tests.

While there is not a significant difference in contract strictness between loans arranged by banks specialized in a given industry and banks that are not specialized, it appears that the former have higher spreads. Moreover, loan agreements between a bank specialized in an industry and a borrower in the industry of specialization display lower amounts, lower maturity and lower number of syndicate members. Even though this is suggestive of a relationship between bank specialization and contract features, this evidence may come simply from the different characteristics of specialized banks and their borrowers.

We pursue the matter further performing t-tests on bank and firm characteristics, similarly to what we do for loans. Specifically, we split all bank-quarter observations into those that are associated with a loan arranged to any sector the bank is specialized in, and those that are not. We do the same for firm-quarter observations.

The mid panel of Table 3 displays the results of the t-tests for firm characteristics. The estimates confirm that firms obtaining loans from banks specialized in their industry are generally different than other firms. They are smaller, less likely to have a long-term issuer credit rating – and therefore less likely to have access to public debt/equity markets – and if they do have a credit rating, it is on average lower. Essentially, a firm that borrows from banks specialized in its own industry is likely to be subject to more severe information frictions. It also displays a higher current ratio, and lower profitability, with respect to firms borrowing from other banks.

The bottom panel of Table 3 shows the estimate of t-tests on bank characteristics.[17] To be clear, a bank can appear both in the "specialized" and "non-specialized" sample at a given moment in time. With this caveat in mind, what emerges is that banks specialized in lending

17. Since the same bank issue more than one loan, the standard errors for the t statistics in Table 3 have been adjusted for clustering at the bank level.

towards a given sector are different compared to other banks. Specifically, they are smaller, have a larger reliance on deposits, and they appear to be better capitalized. However, they do not appear to have larger loan loss allowances nor larger amounts of non-performing assets.

Overall, the evidence in Table 3 suggests that bank specialization might play a role in determining loan characteristics, but any conclusion based on simple univariate analysis would be distorted by the pervasive selection in the matching between borrowers and lenders. In the next Section, we analyze this in a multivariate regression framework with fixed effects.

3.2. Empirical Strategy: a Within-Bank Approach

To retrieve the effect of bank specialization on loan contract strictness, ideally we would like to observe identical firms borrowing from two different banks, one specialized in lending towards the firm's industry and one not specialized. In particular, the firms should be *randomly assigned* to the banks, and each bank should differ from each other only for its specialization status. However, matching between banks and firms is rarely random and loan contract terms are an outcome of this matching process. If, as Table 3 suggests, specialized banks are small banks that in general tap a pool of borrowers which are smaller, more opaque and riskier, any observed variation in the loan contract strictness might just be the direct consequence of the systematically different characteristics of the firms and banks involved.[18]

To mitigate these concerns, we procede in the following way. We start from a within-bank approach, akin to the one proposed at the firm level by Khwaja and Mian (2008). Underlying our empirical strategy there is the idea of comparing two loans arranged by the *same bank* in the *same year*, one issued to a borrower in an industry in which the bank is specialized in lending to, and one issue to a borrower in another industry. This, however, does not fully account for the borrower selection problem. Even after absorbing all bank-specific, time-varying characteristics, it may be the case that within each bank's borrower pool, the firms that fall within the industries in which the bank are specialized are systematically different. To address this, we first include firm balance sheet controls, which absorb variation due to observable and

18. This systematic difference can regard both observable and unobservable characteristics. It is in fact well known in the literature that contract strictness reflects borrower riskiness (Demiroglu and James, 2010), and ex-ante bank confidence in the underwritten loans (Murfin, 2012).

time-varying firm characteristics. Furthermore, we add firm-fixed effects, which account for all firm-specific, observable and unobservable characteristics that are fixed in time.[19]

Formally, we employ the following specification:

$$\begin{aligned} \textit{Loan Contract Term}_{f,b,t} = \alpha + \theta_{b,y(t)} + \textit{Other Fixed Effects} + \beta \cdot \textit{Specialization}_{f,b,t-1} \\ + \gamma_F \cdot \textit{Firm Controls}_{f,t} + \gamma_L \cdot \textit{Loan Controls}_{f,b,t} + \varepsilon_{f,b,t} \end{aligned} \tag{5}$$

in which *Loan Contract Term*$_{f,b,t}$ stands for loan contract strictness, or the all-in-drawn spread, or the all-in-undrawn spread, for a loan originated in quarter t by bank b to firm f. α is the common intercept; $\theta_{b,y(t)}$ represents bank×year fixed effects; the term *Other Fixed Effects* includes borrower fixed effects and separate intercepts for each S&P long-term issuer credit rating, with the omitted dummy variable capturing unrated firms. The main explanatory of interest is included as *Specialization*, a lagged 12-quarters rolling average of the specialization dummy $Spec_{it}^{b}$ (defined in Equation (4)). *Firm Controls* includes firm level proxies of time-varying risk. It includes the Altman Z-score of the borrower at the time of issuance (Altman, 1968), as well as debt to tangible net worth, current ratio, and tangible net worth scaled by total assets. These controls account for repayment risk (especially for non-rated firms), leverage, liquidity, and the firm's ability to provide collateral, and are likely to represent the accounting ratios lenders take into account in their analysis of borrowers (Murfin, 2012).[20] Finally, *Loan Controls* includes also loan-level controls such as logged maturity, logged loan amount and the logged number of syndicate members.

We make the choice to average the specialization dummy over 12 quarters to put less weight on banks that are only sporadically specialized in a sector. This might be simply the result of a single large loan at a time of relative low lending activity in that industry, or measurement error due to the limitations of our dataset. We chose 12 quarters as this length ensures a good balance

19. Ideally, we would rather to have a within bank-time and within firm-time specification. Unfortunately, as we work on a sample of very large loans, we do not see the many firms doing multiple deals in the same year. This makes the adoption of such strategy infeasible.

20. Murfin (2012) uses logged tangible net worth instead of tangible net worth scaled by total assets, and fixed charge coverage ratio, which we do not utilize, as controls. We do not use logged tangible net worth because it would result in a considerably-lower number of observations in our sample (approx 25% of the observations) as tangible net worth can be negative as well—however, repeating the analysis with logged tangible net worth does not change the main results of the paper, and if anything, it makes them stronger. We do not use the fixed charge coverage ratio because it is a ratio that lacks a credible common definition across loan agreements (Demerjian and Owens, 2016, Table 4).

between capturing persistence and avoiding that our measure simply mimics the origination of new loans—the average maturity of a loan in DealScan is around 4 years.[21]

3.3. The Effect of Specialization on Loan Contract Strictness and Pricing

We now introduce the baseline results of our analysis. Table 4 reports the regression estimates of the specification in Equation (5) over the Strictness Sample, for three different loan contract characteristics: Strictness, AISD, and AIUD. Looking at contract strictness first, the estimate on the specialization variable is negative and statistically significant, indicating that banks specializing in lending towards a given industry write less strict contracts when entering loan agreements with firms in that industry. The estimates on loan spreads are overall negative, but their significance and magnitude is more dependent on the specification.

In particular, with respect to loans issued to firms in other industries by the same bank in the same year, a loan contract with a firm in the bank's area of specialization is less strict by 7.5 percentage points (column 1). This estimate is economically significant, as it amounts to 20% of the mean value and to 17% of the standard deviation of the distribution of contract strictness in our sample. Note that this is not associated with higher loan spreads: the estimates on the specialization variable in relation to the all-in-drawn spread is negative and statistically significant (column 4), and in relation to the all-in-undrawn spread the coefficient is positive but very close to zero and not statistically significant (column 7).

In columns 2, 5, and 8, we include borrower and rating fixed effects to further reduce concerns that the effect of specialization just highlighted might be entirely a byproduct of unobserved heterogeneity in borrower types and riskiness. For contract strictness, the estimate on the specialization variable remains statistically significant and is slightly larger in magnitude, while the effect on spreads becomes insignificant.

However, banks specializing in lending towards certain industries might provide credit with credit instruments that are systematically different compared to non specialized banks; e.g. suppose that specialized banks only agree to provide credit in the form of term loans, whereas

21. However, we stress that performing the analysis with a measure of specialization averaged over rolling windows of different length does not change the main results of the paper. At this purpose, we refer to Robustness checks presented in Section 3.6. Finally, we note that the same rolling window's length choice, performed for similar reason, can also be found in Paravisini et al. (2018).

non-specialized banks only in the form of revolving credit. To address this concern we add loan type fixed effects in the baseline specification, and results are reported in columns 3, 6, and 9 of Table 4. The estimates on the specialization variable are virtually unchanged.

The negative, economically and statistically effect of the specialization variable on contract strictness suggests less information asymmetry, or "distance", between a bank specialized in lending towards a given industry and firms in that industry. The negative or null estimates on the same specialization variable when loan spreads are the dependent variables, reinforce this hypothesis, ruling out that lower strictness is compensated with a higher cost of credit, which would weaken the notion of lending advantage. It appears that specialized banks not only leave more leeway to their borrowers, but they appear not to see this "slacker leash" as a risk for which they must be properly compensated. This suggests less restrictive covenant in such cases actually reflect better ex-ante knowledge of the projects/capacity to screen them.

This conclusion is further supported by analyses of the relation between bank specialization and loan spreads conducted over the larger Matched Sample. Table 5 reports the results for the same regressions as in Table 4 – without restricting the sample only to those loan contracts for which a measure of strictness is available – with just all-in-drawn spread and all-in-undrawn spread as dependent variables. In this case, the estimates on the specialization variable when all-in-drawn spread is the dependent variables (columns 1 to 3) are larger, and they are statistically significant even when borrower and rating fixed effects are included in the specification. The estimate is still large but loses significance when loan type fixed effects are included on top of borrower and rating individual dummies. When all-in-undrawn spread is the dependent variable instead the estimates on the specialization variable are basically zero and never statistically significant (columns 4 to 6).

Overall, the evidence presented so far is coherent with explanations of bank specialization based on the existence of lending advantages, and in particular it singles out a specific source of such advantages, namely an industry-specific information advantage.

3.4. Assessing Alternative Explanations

There might be alternative explanations for the results presented in Tables 4 and 5. In particular, the results presented so far are consistent with at least three other economic mechanisms: presence of relationship lending, internalization of externalities that arise when a bank has a large market share in a given industry, and geographic, rather than industry-specific, specialization.

Relationship Lending

First, we could argue that the industry-specific information advantage simply reduces to an information advantage that is borrower-specific. This would be consistent with the observed phenomena of "relationship lending" (Petersen and Rajan, 1994, 1995; Berger and Udell, 1995). For example, recent work by Bharath et al. (2009); Prilmeier (2017) specifically show that relationship lending matters for the determination of covenants and other contract terms in syndicated loan agreements.

To explore the role that borrower-specific information might have on the determination of loan contract strictness, we include in our specification the two empirical proxies for the intensity and length of the bank-firm relationship we described in Section 2. Table 6 reports the results for these regressions. Across all specifications, for both contract strictness and loan spreads, the estimated coefficient on the specialization variable is virtually unchanged – and still statistically significant when considering contract strictness – validating the hypothesis that banks have an information advantage that stems from an industry-specific expertise and not only from borrower-specific information.[22]

In conclusion, we see that an explanation based *only* on relationship lending does not seem appropriate to *fully* rationalize the observed relationship between bank specialization and the existence of an information advantage relative to that industry.

22. This does not imply at all that relationship lending is not important. As Prilmeier (2017), we do find evidence that the longer a bank-firm relationship, the lower strictness and all-in-drawn spread associated with the contract. Yet, this is true only when considering a within-bank approach. With the inclusion borrower and rating fixed effects this effect disappears. This result is not surprising, given that there is probably little variation in those variables within-firm, also in light of the small number of banks a firm interacts with in our sample. Further discrepancies between ours and Prilmeier (2017)'s findings (e.g. the lower power of the relationship intensity's coefficient) are explained by the different measure of covenant strictness we use.

Specialized Banks as High-Market-Share Lenders

Second, we might be concerned that if banks are specialized in lending towards a given industry, those banks are also the one providing a relatively large share of credit to that industry, i.e. they have a high market share in that industry. The literature points out that this could be an alternative mechanism explaining our findings. Giannetti and Saidi (2018) show that banks that have a high market share in an industry are more likely to internalize negative spillovers and possible systemic effects of tougher credit conditions in that industry – as well as upstream and downstream the relative supply chain – in periods of distress. For analogous reasons, they might have incentives to write less strict contracts to avoid triggering covenant violations that might potentially be costly not only for the specific firm – in terms of investment for example – but also for the entire industry the firm is part of.

To control for this issue, we include in our specifications the variable *Market Share*, defined in Section 2, which is exactly the share of credit outstanding that a bank has in one industry relative to the total credit supplied to the industry by all banks. Table 7 reports the results for these regressions. When looking at contract strictness, the estimates on the specialization variable are still negative, statistically significant, and 1-2 percentage points larger in magnitude. For loan spreads, we still observe negative or null effect of the specialization variable, confirming the results of the main analysis.

Turning to the effect of a high market share on contract strictness, we can see that the estimated coefficient for the market share variable is positive and highly significant. We have two possible explanations for this relation. First, it may be a result of the fact that banks with high market share in an industry have a larger pool of loans in that industry by construction. As a consequence, their marginal borrower is of lower quality, has higher information distance from its lender, and receives stricter covenants. Second, it may be the case that these banks have overall higher market power, which increases their charter value, making them less willing to take risks (Keeley, 1990).

Geographical Proximity

Third, the literature points to the role of geographic distance as an important proxy for the degree of asymmetric information between borrowers and lenders. Loan terms are more favorable when borrowers are geographically closer to lenders (Agarwal and Hauswald, 2010; Alessandrini et al., 2008; Degryse and Ongena, 2005), even in market of large corporations (Hollander and Verriest, 2016).

We are thus concerned that banks specialized in lending towards a given industry have an abnormal exposure to that industry because they are lending to specific locations that feature business concentration in that industry and that are geographically close to these banks' headquarters. This geographical proximity between banks and firms in specific industries might in turn explain our results. If this is the case, we would still interpret our result in light of an information advantage of these banks. However, this advantage would not stem from an industry-specific expertise, but from the acquisition of soft information guaranteed by geographical proximity. To address this issue, we construct a dummy variable, *Same State*, which takes value 1 if the bank and the firm headquarters are located in the same state, and we include it in our specifications.

Table 8 presents the results for these regressions. Consistent with the notion that geographical proximity between borrowers and lenders reflects a lower level of asymmetric information, the estimates on the same-state dummy are negative for both contract strictness and loan spreads. However, they are not significant or only marginally so. On the other hand, the estimated coefficients on the specialization variable are essentially the same as the baseline specifications.

Finally, Table 9 reports the results of regressions that includes all aforementioned controls for relationship lending, market share and geographical proximity. The coefficients on the specialization variables across various specifications with the different loan terms as dependent variable are unchanged or slightly larger in magnitude, and consistent with the baseline estimates. Overall, none of these possible alternative explanations appears able to rule out the important role of bank specialization in determining covenant strictness, nor the information advantage interpretation we are providing for it.

3.5. Specialization and Defaults on Lender Portfolios

To provide further evidence in support of our proposed interpretation, inspired by Murfin (2012), we employ defaults on lender loan portfolios as a relatively exogenous shock to the lenders' perception of their own screening ability. We examine whether default of firms from industry x in the portfolio of bank b affect differentially banks that are specialized in lending to x and banks that are not. In particular, we focus on how the pricing and covenant strictness change for loans underwritten after the defaults.

To do so, we compute the number of defaults each bank experiences in its loan portfolio by counting the times any given borrower, among those the bank has an active credit relationship with, has a credit rating of "D" or "SD" over a period of time that ranges from 90 to 360 days.[23] Suppose it is indeed true that banks specialized in lending towards one sector have an information advantage in screening or monitoring specific projects in that industry. We posit that, for a given number of defaults on a lender portfolio that occur to borrower in a that industry, banks specialized in lending towards that industry would *revise more* the perception of their own ability of screening borrowers in that industry, compared to banks not specialized in lending towards that industry. In fact, a default in a given industry should be relatively more informative for those banks who have an information advantage for that given industry. If defaults occur in industries out of a bank's area of specialization, on the other hand, we should not observe any differential revision of a bank's own screening ability.

We empirically test this implication by employing a specification similar to the one in Equation (5), with the inclusion of interaction terms between the specialization variable and the number of defaults on lender portfolio, as follows:

$$\begin{aligned} \textit{Loan Terms}_{f,b,t} = \alpha + \theta_b + \theta_t + \textit{Fixed Effects} + \beta \cdot \textit{Specialization}_{f,b,t-1} \\ + \gamma_D \cdot \textit{Defaults}_{b,t-1} + \rho \cdot \textit{Specialization}_{f,b,t-1} \times \textit{Defaults}_{b,t-1} \\ + \gamma_B \cdot \textit{Bank Controls}_{b,t} + \gamma_F \cdot \textit{Firm Controls}_{f,t} + \gamma_L \cdot \textit{Loan Controls}_{f,b,t} + \varepsilon_{f,b,t} \end{aligned} \tag{6}$$

The specification in Equation (6) does not include neither bank×year fixed effects nor

23. See Murfin (2012) for more details on why to employ those time intervals.

borrower fixed effects as there would not be enough variation of specialization *and* defaults within those groups.[24] Instead, we include additive time and bank fixed effects, and we saturate the regressions with several bank time-varying controls, such as logged bank assets, the ratio of deposits over total assets, bank book capitalization, the share of non-performing assets over total assets, and the amount of loan loss allowances scaled by total assets. We also keep credit rating fixed effects and loan type fixed effects.

The coefficient of interest is ρ, which measures the differential effect on loan contract terms of a specialized banks in response to one more default with respect to a non specialized bank. In particular, given a loan agreement between a bank b and a firm f that starts at time t, we are going to consider two different types of *Defaults* variable: *Defaults (same)*, which denotes only the defaults that have occurred in the same industry as f, and *Defaults (other)*, which considers the total number of defaults occurred in all other industries. Crucially, we expect a positive and significant effect only for the interaction term of the specialization variable and *Defaults (same)*, but not for the interaction term with *Defaults (other)*. This amount to saying the following: a bank that is specialized in lending towards industry i, when lending to a borrower in industry i, is going to be more responsive – relative to a bank that is lending to the same industry – only when it experiences borrower defaults in industry i, and not when the defaults occur in any other industry.

Table 10 shows the results of regressions as in Equation (6), and the evidence is consistent with our hypotheses. The top panel in particular displays regressions in which the variable *Defaults* is computed by counting defaults in lender portfolios that occurred over a period of 90 days prior to the start date of a loan, whereas in the bottom panel the variable *Defaults* is computed by looking at a period of 360 days prior to the start date of a loan. As in previous tables, columns 1 to 3 focus on contract strictness and columns 4 to 6 on all-in-drawn spread.

From this table two patterns emerge. Specialized banks do not write stricter contracts nor charge higher spreads with respect to non specialized bank when the defaults occur in industries out of their area of specialization, and when dealing with borrowers in these other

24. For example, the total number of bank-year groups in the sample is 476. Out of these, we observe variation in both specialization *and* defaults only in 28 groups. If we consider bank fixed effects, out of the 60 present in the sample, we find variation of both specialization *and* default in 31 groups. Considering borrower fixed effects, out of the $2,836$ firms, we have within-firm variation in both specialization and default only in 75 cases.

industries. However, banks specialized in lending to one industry charge higher spreads, relative to non specialized banks, when lending to their industry of specialization and after experiencing defaults in that industry.

The estimate on the interaction term between the specialization variable and *Defaults (90d, same)* is positive and statistically significant. For each default that a specialized bank experiences in its area of specialization, it charges borrowers in that industry an all-in-drawn spread that is 10 basis points higher compared to a non-specialized bank that lends to the same industry. Specialized banks do not appear to write proportionally stricter loan contracts. However, this is true only when considering defaults on lender portfolios that are relatively close in time, that is for defaults occurring in the 90 days prior the start date of a loan.

If we turn to a larger time-horizon to compute the defaults, namely 360 days, we find a positive and statistically significant effect of the interaction term between the specialization variable and *Defaults (360d, same)* on loan contract strictness. The effect on the all-in-drawn spread is instead attenuated and not statistically significant. A potential explanation for these patterns is that at first banks that are specialized in an industry react more to defaults in their industry of specialization by charging higher spreads, and only after a longer period of time, they start updating the perception of their own screening ability, and write stricter contracts.

3.6. Robustness Checks

The results stand to a series of robustness checks. First, omitting or including loan-level controls leaves the results for the baseline analysis unchanged, and if anything the results are stronger, as can be seen in Table 11. Second, averaging the specialization dummy defined in Equation (4) over different time horizon does not change the main message of the paper. As can be seen in Table 12, the effect of the specialization variable is attenuated when averaging over 4 or 8 quarters (1 or 2 years), but remain generally consistent in magnitude. The lower and mostly non-statistically significant estimates that we obtain when averaging the specialization dummy over a period of 1 an 2 year actually represent an indirect validation of our proposed mechanism. It takes time to build expertise that is industry-specific, and therefore estimates are more reliable and precise once the average of the specialization dummy is taken over longer periods. Third, considering only the loans with at most 5 or at most 1 lead arranger(s) – the baseline being all loans with at most 10 lead arrangers – actually makes the results stronger, as can be seen in Table 13. Fourth and last, changing some of the firm-level controls in the regressions, for example including book leverage and logged firm assets in lieu of debt to tangible net worth and tangible net worth over total assets, yields very similar estimates across most specifications, as can be seen in Table 14.

4. Conclusion

In this paper we provide evidence that banks specialize in lending toward specific industries even in a credit market for large borrowers, such as the US syndicated loan market. We show that loan contracts between borrowers in an industry and banks specialized in lending towards that industry display a less restrictive covenant structure and no higher spreads. This, comparing two loans made by the same bank in the same year, one towards the industry of specialization and one to any other industry. We show that this result cannot be fully explained by borrower risk, or other phenomena such as relationship lending, the ability of lenders to internalize the spillovers effects of their credit decision within an industry, or geographical proximity.

Interpreting the restrictiveness of the covenant structure as the degree of information asymmetry between a borrower and a lender, we conclude that a potential source of the lending advantage associated with specialization is represented by an information advantage. This carries implications for the understanding of competition and monopoly power in credit markets, and thus for the transmission mechanism of monetary policy and potential heterogeneous effects of regulation. These are all potential avenues for future research.

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Appendix A. Tables

Table 1. Distribution of Bank Lending Shares by Industry

	$L_{it}^{b} - \bar{L}_{it}$				
	Min	Median	Max	Std. Dev.	Skewness
2	-0.113	-0.027	0.710	0.136	2.015
3	-0.152	-0.019	0.842	0.065	4.439
4	-0.117	-0.031	0.515	0.102	3.800
5	-0.316	-0.059	0.755	0.166	1.557
6	-0.200	-0.041	0.788	0.094	2.457
7	-0.126	-0.015	0.732	0.081	2.201
8	-0.197	-0.054	0.781	0.162	1.928
9	-0.126	-0.046	0.239	0.044	1.781
10	-0.164	-0.040	0.884	0.112	4.524
11	-0.183	-0.042	0.718	0.081	2.208
12	-0.137	-0.036	0.867	0.106	5.612
13	-0.149	-0.042	0.930	0.112	2.747
14	-0.131	-0.013	0.785	0.087	3.598
15	-0.108	-0.016	0.829	0.067	3.144
16	-0.114	-0.032	0.884	0.081	4.505
17	-0.134	-0.037	0.520	0.082	2.798
18	-0.126	-0.021	0.875	0.068	4.376
19	-0.100	-0.021	0.664	0.069	5.267
20	-0.163	-0.013	0.879	0.076	6.202
21	-0.093	-0.021	0.804	0.057	10.022
22	-0.165	-0.046	0.916	0.074	5.676
23	-0.086	-0.010	0.401	0.045	5.817
24	-0.071	-0.034	0.797	0.065	7.129
25	-0.126	-0.037	0.921	0.061	7.665
26	-0.110	-0.026	0.179	0.044	1.714
Total	-0.316	-0.034	0.930	0.112	2.596

Table 2. Descriptive Statistics

	MATCHED SAMPLE			STRICTNESS SAMPLE		
	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.
Loan variables						
Contract Strictness	36.57	41.29	11,223	36.57	41.29	11,223
Number of Covenants	1.38	1.49	25,912	2.52	1.15	11,223
All-In Drawn Spread	188.18	133.11	22,379	188.00	124.35	10,777
All-In Undrawn Spread	24.85	19.51	16,523	26.18	18.37	9,257
Loan Amount ($ M)	627.48	1483.63	25,911	519.60	1085.89	11,223
Maturity (Months)	47.00	26.29	24,364	45.07	20.75	11,136
Syndicate Size	7.75	8.74	25,912	9.10	9.77	11,223
Relationship Length	1.83	3.18	25,912	1.76	3.00	11,223
Performance Pricing	0.40	0.48	25,912	0.68	0.45	11,223
Firm variables						
Log(Assets)	7.09	1.95	22,958	6.70	1.84	10,662
Rated	0.52	0.50	23,138	0.48	0.50	10,721
Rating	10.28	3.46	11,931	10.80	3.08	5,126
Book Leverage	30.63	22.61	22,138	30.82	22.18	10,338
Debt/Tangible Net Worth	0.98	80.81	14,214	0.34	20.25	6,445
Tangible Net Worth/Assets	0.19	0.50	14,640	0.20	0.31	6,611
Risky Borrower	0.53	0.50	20,228	0.53	0.50	9,512
Current Ratio	1.98	3.14	22,099	1.92	1.64	10,352
Profitability	0.03	0.05	21,620	0.03	0.04	10,020
N. Loans	10.05	8.23	23,138	9.27	7.15	10,721
N. Credit Relationships	3.79	2.86	23,138	3.48	2.46	10,721
Bank variables						
Log(Assets)	12.29	1.64	2,053	12.12	1.61	1,487
Deposits/Assets	61.82	13.17	2,043	61.76	12.86	1,480
Book Equity	7.27	2.69	2,010	7.41	2.56	1,467
Market Equity	12.42	5.82	514	12.38	6.22	366
Tier 1 Capital Ratio	9.68	2.26	1,889	9.26	2.11	1,407
Non-Performing Assets	0.68	0.62	1,714	0.64	0.55	1,302
Loan Losses Allowance	0.96	0.48	1,959	1.00	0.47	1,439
N. Loans Arranged	567.44	1073.41	3,151	695.01	1202.93	2,155

Table 3. Univariate Evidence on Loan Contracts and Bank-Firm Selection

	Spec.	Non Spec.	Diff.	t-Stat	N (Spec.)	N (Non Spec.)
Loan variables						
Contract Strictness	36.26	35.46	0.80	0.48	648	9864
Number of Covenants	1.37	1.33	0.04	1.12	1588	23295
All-In Drawn Spread	224.12	184.77	39.34	10.14	1268	19970
All-In Undrawn Spread	25.85	24.63	1.22	1.72	816	14901
Loan Amount ($ M)	518.67	680.40	-161.73	-4.04	1588	23294
Maturity (Months)	45.87	48.16	-2.29	-3.13	1492	21979
Syndicate Size	6.05	8.06	-2.01	-8.95	1588	23295
Relationship Length	1.95	1.84	0.12	1.43	1588	23295
Performance Pricing	0.30	0.40	-0.10	-8.32	1588	23295
Firm variables						
Log(Assets)	6.61	7.35	-0.74	-14.63	1569	23101
Rated	0.45	0.56	-0.11	-8.58	1588	23295
Rating	10.87	10.23	0.64	4.85	713	13033
Book Leverage	30.66	31.62	-0.96	-1.60	1491	22341
Debt/Tangible Net Worth	0.82	3.77	-2.95	-0.48	839	14785
Tangible Net Worth/Assets	0.17	0.18	-0.01	-0.60	868	15175
Risky Borrower	0.54	0.54	-0.01	-0.66	1390	20371
Current Ratio	2.49	1.90	0.58	5.80	1511	22241
Profitability	0.02	0.03	-0.01	-11.21	1441	21834
Banks variables						
Log(Assets)	11.4	13.3	-1.85	-2.67	1184	19129
Deposits/Assets	66.8	54.9	11.9	2.57	1180	19097
Book Equity	8.15	7.65	0.50	0.84	1168	18962
Market Equity	11.8	9.85	1.96	2.17	238	8038
Tier 1 Capital Ratio	10.1	9.26	0.87	1.00	1131	18755
Non-Performing Assets	0.63	0.61	0.016	0.19	1056	17823
Loan Losses Allowance	1.10	0.99	0.11	1.21	1139	18736

Table 4. The Effect of Bank Specialization on Loan Contract Terms

	CONTRACT STRICTNESS			ALL-IN DRAWN SPREAD			ALL-IN UNDRAWN SPREAD		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Specialization	-7.477**	-8.319**	-8.34**	-18.66**	-1.144	-5.319	2.022	3.944	3.652
	(-2.08)	(-2.17)	(-2.16)	(-2.10)	(-0.10)	(-0.52)	(0.69)	(1.19)	(1.12)
Borrower Z-Score	-4.492***	-3.234***	-3.221***	-15.91***	-8.898***	-8.775***	-2.213***	-1.146***	-1.123***
	(-12.72)	(-5.00)	(-5.02)	(-8.95)	(-5.37)	(-5.36)	(-7.40)	(-3.43)	(-3.41)
Debt/Tang. Net Worth	-.0192	-.0161	-.0154	-.0613*	-.0183	-.0244	-.0133	-.0288***	-.0272***
	(-0.93)	(-0.40)	(-0.39)	(-2.01)	(-0.51)	(-0.85)	(-1.48)	(-3.84)	(-3.45)
Tang. Net Worth/Assets	-5.069*	-10.2	-10.35	-48.7***	-31.76***	-29.29***	6.55***	5.488**	5.591**
	(-1.76)	(-1.58)	(-1.59)	(-4.33)	(-3.08)	(-2.75)	(3.95)	(2.47)	(2.50)
Current Ratio	-.224	-2.372*	-2.357*	9.582***	-.7693	-1.644	1.128*	-1.677	-1.651
	(-0.38)	(-1.77)	(-1.79)	(3.65)	(-0.49)	(-0.93)	(1.73)	(-1.07)	(-1.06)
Bank-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Rating FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Loan Type FE	No	No	Yes	No	No	Yes	No	No	Yes
Adj. R^2	.18	.526	.527	.41	.662	.683	.262	.558	.57
N. Banks	36	35	35	35	34	34	35	33	33
Observations	5484	4740	4740	5283	4549	4549	4526	3810	3810

This table reports the estimates of the coefficients from the following regression over our baseline sample, which includes only loans for which the contract strictness measure is available:

$$Loan\ Contract\ Term_{f,b,t} = \alpha + \theta_{b,t} + Fixed\ Effects + \beta \cdot Specialization_{f,b,t-1} + \beta_F \cdot Firm\ Controls_{f,t} + \beta_L \cdot Loan\ Controls_{f,b,t} + \varepsilon_{f,b,t}$$

in which *Loan Contract Term*$_{f,b,t}$ is either CONTRACT STRICTNESS (columns 1 to 3), ALL-IN DRAWN SPREAD (columns 4 to 6), and ALL-IN UNDRAWN SPREAD (columns 7 to 9) for a loan originated in time t by bank b to firm f. α is the common intercept, $\theta_{b,t}$ represents bank×time fixed effects, and *Fixed Effects* include, depending on the specification, firm fixed effects, rating (time-varying) fixed effects and/or loan type fixed effects . *Specialization* is a lagged 3-year rolling average of the specialization dummy for bank b in the sector of firm f. Firm controls include the z-score, current ratio, the ratio of tangible net worth over total assets, and the ratio of debt over tangible net worth. Loan controls include logarithms of maturity, number of participants and of the deal amount, and they are included in the specification for each column. In parentheses, t statistics obtained from clustering at the bank level. ***, **, * indicate statistical significance at the 1%, 5% and 10%, respectively.

Table 5. The Effect on Bank Specialization on Loan Pricing Terms over the Full Sample

	All-In Drawn Spread			All-In Undrawn Spread		
	(1)	(2)	(3)	(4)	(5)	(6)
Specialization	-20.04*	-21.78**	-15.72	.6438	1.695	1.46
	(-1.81)	(-2.15)	(-1.61)	(0.29)	(0.79)	(0.69)
Borrower Z-Score	-12.41***	-5.895***	-5.644***	-1.914***	-.7445***	-.7592***
	(-10.46)	(-6.93)	(-7.74)	(-8.55)	(-3.25)	(-3.61)
Debt/Tang. Net Worth	.0141***	.0159***	.0149***	-.0048	-.0143*	-.0139
	(7.47)	(12.29)	(14.21)	(-0.72)	(-1.70)	(-1.59)
Tang. Net Worth/Assets	-60.99***	-49.16***	-47.45***	5.319***	.8307	1.029
	(-10.96)	(-4.39)	(-4.79)	(3.98)	(0.49)	(0.71)
Current Ratio	9.186***	3.43**	2.696	1.031***	-.2677	-.2255
	(5.41)	(2.22)	(1.65)	(3.25)	(-0.54)	(-0.46)
Bank-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	No	Yes	Yes
Rating FE	No	Yes	Yes	No	Yes	Yes
Loan Type FE	No	No	Yes	No	No	Yes
Adj. R^2	.374	.608	.638	.229	.541	.553
N. Banks	44	42	42	41	38	38
Observations	11362	10541	10541	8374	7554	7554

This table reports the estimates of the coefficients from the following regression over our baseline sample, which includes only loans for which the contract strictness measure is available:

$$Loan\ Spread_{f,b,t} = \alpha + \theta_{b,t} + Fixed\ Effects + \beta \cdot Specialization_{f,b,t-1} + \beta_F \cdot Firm\ Controls_{f,t} + \beta_L \cdot Loan\ Controls_{f,b,t} + \varepsilon_{f,b,t}$$

in which *Loan Spread_f,b,t* is either ALL-IN DRAWN SPREAD (columns 1 to 3), and ALL-IN UNDRAWN SPREAD (columns 4 to 6) for a loan originated in time t by bank b to firm f. α is the common intercept, $\theta_{b,t}$ represents bank×time fixed effects, and *Fixed Effects* include, depending on the specification, firm fixed effects, rating (time-varying) fixed effects and/or loan type fixed effects . *Specialization* is a lagged 3-year rolling average of the specialization dummy for bank b in the sector of firm f. Firm controls include the z-score, current ratio, the ratio of tangible net worth over total assets, and the ratio of debt over tangible net worth. Loan controls include logarithms of maturity, number of participants and of the deal amount, and they are included in the specification for each column. In parentheses, t statistics obtained from clustering at the bank level. ***, **, * indicate statistical significance at the 1%, 5% and 10%, respectively.

Table 6. The Effect of Bank Specialization on Loan Contract Terms, controlling for Bank-Firm Relationships

	CONTRACT STRICTNESS			ALL-IN DRAWN SPREAD			ALL-IN UNDRAWN SPREAD		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Specialization	-7.147*	-8.321**	-8.347**	-16.74*	-.8305	-5.197	1.996	3.986	3.7
	(-1.96)	(-2.15)	(-2.15)	(-1.82)	(-0.07)	(-0.50)	(0.67)	(1.19)	(1.12)
Rel. Intensity	.821	.8266	.8867	.5224	-6.173	-5.679	1.725***	-.0103	-.011
	(0.79)	(0.69)	(0.75)	(0.11)	(-1.58)	(-1.40)	(3.43)	(-0.01)	(-0.01)
Rel. Length	-.4438***	-.166	-.1593	-2.091***	.2887	.6085	-.1155	-.1162	-.1428**
	(-3.78)	(-1.52)	(-1.38)	(-5.00)	(0.58)	(1.03)	(-1.65)	(-1.63)	(-2.21)
Bank-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Rating FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Loan Type FE	No	No	Yes	No	No	Yes	No	No	Yes
Adj. R^2	.181	.526	.527	.412	.662	.683	.263	.558	.57
N. Banks	36	35	35	35	34	34	35	33	33
Observations	5484	4740	4740	5283	4549	4549	4526	3810	3810

This table reports the estimates of the coefficients from the following regression over our baseline sample, which includes only loans for which the contract strictness measure is available:

$$\begin{aligned} \textit{Loan Contract Term}_{f,b,t} &= \alpha + \theta_{b,t} + \textit{Fixed Effects} + \beta \cdot \textit{Specialization}_{f,b,t-1} + \beta_1 \cdot \textit{Rel. Length}_{f,b,t-1} + \beta_2 \cdot \textit{Rel. Intensity}_{f,b,t-1} \\ &+ \beta_F \cdot \textit{Firm Controls}_{f,t} + \beta_L \cdot \textit{Loan Controls}_{f,b,t} + \varepsilon_{f,b,t} \end{aligned}$$

in which *Loan Contract Term*$_{f,b,t}$ is either CONTRACT STRICTNESS (columns 1 to 3), ALL-IN DRAWN SPREAD (columns 4 to 6), and ALL-IN UNDRAWN SPREAD (columns 7 to 9) for a loan originated in time t by bank b to firm f. α is the common intercept, $\theta_{b,t}$ represents bank×time fixed effects, and *Fixed Effects* include, depending on the specification, firm fixed effects, rating (time-varying) fixed effects and/or loan type fixed effects . *Specialization* is a lagged 3-year rolling average of the specialization dummy for bank b in the sector of firm f. *Rel. Length* is the time elapsed between firm f first interaction with the lead arranger b in the DealScan database and the current loan – originated at time t. *Rel. Intensity* is the ratio between the total amount of credit firm f received from bank b over the past 5 years, and the total amount of credit received by firm f over the same period, excluding the current loan. Firm controls include the z-score, current ratio, the ratio of tangible net worth over total assets, and the ratio of debt over tangible net worth. Loan controls include logarithms of maturity, number of participants and of the deal amount, and they are included in the specification for each column. In parentheses, t statistics obtained from clustering at the bank level. ***, **, * indicate statistical significance at the 1%, 5% and 10%, respectively.

Table 7. The Effect of Bank Specialization on Loan Contract Terms, controlling for Bank Market Share

	Contract Strictness			All-In Drawn Spread			All-In Undrawn Spread		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Specialization	-9.273**	-9.872**	-9.905**	-20.56**	-.956	-5.718	1.285	3.3	3.076
	(-2.69)	(-2.51)	(-2.51)	(-2.44)	(-0.09)	(-0.58)	(0.43)	(1.01)	(0.95)
Market Power	15.51***	11.71***	11.77***	16.74	-1.522	3.212	7.051**	6.244***	5.633**
	(4.10)	(3.97)	(4.15)	(0.95)	(-0.06)	(0.12)	(2.52)	(3.34)	(2.49)
Bank-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Rating FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Loan Type FE	No	No	Yes	No	No	Yes	No	No	Yes
Adj. R^2	.181	.527	.528	.411	.662	.683	.263	.558	.57
N. Banks	36	35	35	35	34	34	35	33	33
Observations	5484	4740	4740	5283	4549	4549	4526	3810	3810

This table reports the estimates of the coefficients from the following regression over our baseline sample, which includes only loans for which the contract strictness measure is available:

$$\begin{aligned} \textit{Loan Contract Term}_{f,b,t} = \alpha + \theta_{b,t} + \textit{Fixed Effects} + \beta \cdot \textit{Specialization}_{f,b,t-1} + \beta_M \cdot \textit{Market Share}_{f,b,t-1} \\ + \beta_F \cdot \textit{Firm Controls}_{f,t} + \beta_L \cdot \textit{Loan Controls}_{f,b,t} + \varepsilon_{f,b,t} \end{aligned}$$

in which *Loan Contract Term*$_{f,b,t}$ is either CONTRACT STRICTNESS (columns 1 to 3), ALL-IN DRAWN SPREAD (columns 4 to 6), and ALL-IN UNDRAWN SPREAD (columns 7 to 9) for a loan originated in time t by bank b to firm f. α is the common intercept, $\theta_{b,t}$ represents bank×time fixed effects, and *Fixed Effects* include, depending on the specification, firm fixed effects, rating (time-varying) fixed effects and/or loan type fixed effects . *Specialization* is a lagged 3-year rolling average of the specialization dummy for bank b in the sector of firm f. *Market Share* is the ratio between the credit provided by bank b to the industry firm f belongs to and the total amount of credit received by all firms operating in the same industry as firm f, at time $t-1$. Firm controls include the z-score, current ratio, the ratio of tangible net worth over total assets, and the ratio of debt over tangible net worth. Loan controls include logarithms of maturity, number of participants and of the deal amount, and they are included in the specification for each column. In parentheses, t statistics obtained from clustering at the bank level. ***, **, * indicate statistical significance at the 1%, 5% and 10%, respectively.

Table 8. The Effect of Bank Specialization on Loan Contract Terms, controlling for Geographical Proximity

	Contract Strictness			All-In Drawn Spread			All-In Undrawn Spread		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Specialization	-7.467**	-8.283**	-8.3**	-18.12*	-1.115	-5.276	2.178	3.944	3.652
	(-2.06)	(-2.12)	(-2.11)	(-2.03)	(-0.10)	(-0.51)	(0.75)	(1.19)	(1.12)
Same State	-.1656	-4.743	-4.749	-8.69	-10.3*	-10.9*	-1.598	-.8309	-.648
	(-0.08)	(-1.61)	(-1.61)	(-1.38)	(-1.79)	(-1.77)	(-1.50)	(-0.77)	(-0.55)
Bank-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Rating FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Loan Type FE	No	No	Yes	No	No	Yes	No	No	Yes
Adj. R^2	.18	.527	.527	.411	.662	.683	.263	.558	.569
N. Banks	36	35	35	35	34	34	35	33	33
Observations	5484	4740	4740	5283	4549	4549	4526	3810	3810

This table reports the estimates of the coefficients from the following regression over our baseline sample, which includes only loans for which the contract strictness measure is available:

$$\begin{aligned} \textit{Loan Contract Term}_{f,b,t} &= \alpha + \theta_{b,t} + \textit{Fixed Effects} + \beta \cdot \textit{Specialization}_{f,b,t-1} + \beta_S \cdot \textit{Same State}_{f,b,t-1} \\ &+ \beta_F \cdot \textit{Firm Controls}_{f,t} + \beta_L \cdot \textit{Loan Controls}_{f,b,t} + \varepsilon_{f,b,t} \end{aligned}$$

in which *Loan Contract Term*$_{f,b,t}$ is either CONTRACT STRICTNESS (columns 1 to 3), ALL-IN DRAWN SPREAD (columns 4 to 6), and ALL-IN UNDRAWN SPREAD (columns 7 to 9) for a loan originated in time t by bank b to firm f. α is the common intercept, $\theta_{b,t}$ represents bank×time fixed effects, and *Fixed Effects* include, depending on the specification, firm fixed effects, rating (time-varying) fixed effects and/or loan type fixed effects . *Specialization* is a lagged 3-year rolling average of the specialization dummy for bank b in the sector of firm f. *Same State* is a dummy that takes value 1 if bank b and firm f are headquartered in the same state, and 0 otherwise. Firm controls include the z-score, current ratio, the ratio of tangible net worth over total assets, and the ratio of debt over tangible net worth. Loan controls include logarithms of maturity, number of participants and of the deal amount, and they are included in the specification for each column. In parentheses, t statistics obtained from clustering at the bank level. ***, **, * indicate statistical significance at the 1%, 5% and 10%, respectively.

Table 9. The Effect of Bank Specialization on Loan Contract Terms, controlling for Bank-Firm Rels., Market Share, and Geo. Prox.

	CONTRACT STRICTNESS			ALL-IN DRAWN SPREAD			ALL-IN UNDRAWN SPREAD		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Specialization	-8.96**	-9.822**	-9.855**	-17.93*	-17.31*	-13.15	-.2309	1.021	.9059
	(-2.55)	(-2.43)	(-2.43)	(-1.69)	(-1.70)	(-1.31)	(-0.10)	(0.48)	(0.42)
Rel. Intensity	.635	.7013	.7633	-10.55**	-16.3***	-12.29***	.5623	-.012	-.097
	(0.61)	(0.59)	(0.65)	(-2.42)	(-4.33)	(-3.44)	(0.78)	(-0.02)	(-0.14)
Rel. Length	-.4538***	-.1549	-.1473	-3.019***	-1.458***	-.7716***	-.0886	.045	.0344
	(-3.90)	(-1.44)	(-1.30)	(-8.63)	(-4.64)	(-3.07)	(-0.57)	(0.63)	(0.45)
Market Power	15.93***	11.63***	11.66***	25.09*	.5519	.9313	7.7***	5.455***	4.657***
	(4.05)	(3.97)	(4.15)	(1.81)	(0.04)	(0.07)	(4.56)	(5.35)	(4.29)
Same State	-.0342	-4.71	-4.725	-11.18**	-3.752	-6.185	-.4033	.4631	.364
	(-0.02)	(-1.61)	(-1.60)	(-2.17)	(-0.68)	(-1.20)	(-0.34)	(0.37)	(0.28)
Bank-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Rating FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Loan Type FE	No	No	Yes	No	No	Yes	No	No	Yes
Adj. R^2	.182	.527	.528	.382	.611	.64	.23	.541	.553
N. Banks	36	35	35	44	42	42	41	38	38
Observations	5484	4740	4740	11362	10541	10541	8374	7554	7554

This table reports the estimates of the coefficients from the following regression over our baseline sample, which includes only loans for which the contract strictness measure is available:

$$\begin{aligned} \textit{Loan Contract Term}_{f,b,t} = {} & \alpha + \theta_{b,t} + \textit{Fixed Effects} + \beta \cdot \textit{Specialization}_{f,b,t-1} + \beta_1 \cdot \textit{Rel. Length}_{f,b,t-1} + \beta_2 \cdot \textit{Rel. Intensity}_{f,b,t-1} \\ & + \beta_M \cdot \textit{Market Share}_{f,b,t-1} + \beta_S \cdot \textit{Same State}_{f,b,t-1} + \beta_F \cdot \textit{Firm Controls}_{f,t} + \beta_L \cdot \textit{Loan Controls}_{f,b,t} + \varepsilon_{f,b,t} \end{aligned}$$

in which *Loan Contract Term*$_{f,b,t}$ is either CONTRACT STRICTNESS (columns 1 to 3), ALL-IN DRAWN SPREAD (columns 4 to 6), and ALL-IN UNDRAWN SPREAD (columns 7 to 9) for a loan originated in time t by bank b to firm f. α is the common intercept, $\theta_{b,t}$ represents bank×time fixed effects, and *Fixed Effects* include, depending on the specification, firm fixed effects, rating (time-varying) fixed effects and/or loan type fixed effects . *Specialization* is a lagged 3-year rolling average of the specialization dummy for bank b in the sector of firm f. *Rel. Length* is the time elapsed between firm f first interaction with the lead arranger b in the DealScan database and the current loan – originated at time t. *Rel. Intensity* is the ratio between the total amount of credit firm f received from bank b over the past 5 years, and the total amount of credit received by firm f over the same period, excluding the current loan. *Market Share* is the ratio between the credit provided by bank b to the industry firm f belongs to and the total amount of credit received by all firms operating in the same industry as firm f, at time $t-1$. *Same State* is a dummy that takes value 1 if bank b and firm f are headquartered in the same state, and 0 otherwise. Firm controls include the z-score, current ratio, the ratio of tangible net worth over total assets, and the ratio of debt over tangible net worth. Loan controls include logarithms of maturity, number of participants and of the deal amount, and they are included in the specification for each column. In parentheses, t statistics obtained from clustering at the bank level. ***, **, * indicate statistical significance at the 1%, 5% and 10%, respectively.

Table 10. Evidence from Defaults on Lender Portfolios

	Contract Strictness			All-In Drawn Spread		
	(1)	(2)	(3)	(4)	(5)	(6)
Defaults on Lender Portfolios (90 days)						
Defaults (90d, other)	.037		.0266	-.3951		-.4065
	(0.19)		(0.14)	(-0.73)		(-0.73)
Specialization × Defaults (90d, other)	.7138		.7643	4.777		4.667
	(0.29)		(0.31)	(0.75)		(0.74)
Defaults (90d, same)		1.151*	1.145*		1.665	1.858
		(1.76)	(1.85)		(0.89)	(0.93)
Specialization × Defaults (90d, same)		-.6677	-.7034		10.78***	9.627**
		(-0.53)	(-0.56)		(2.93)	(2.40)
Specialization	-4.944	-4.606	-4.971	-17.88	-16.29	-18.44
	(-0.96)	(-0.87)	(-0.95)	(-1.18)	(-1.15)	(-1.21)
Adj. R^2	.238	.238	.238	.474	.474	.474
N. Banks	29	29	29	31	31	31
Observations	4472	4472	4472	8933	8933	8933
Defaults on Lender Portfolios (360 days)						
Defaults (360d, other)	-.102*		-.0985*	-.0493		-.0528
	(-2.04)		(-1.95)	(-0.19)		(-0.21)
Specialization × Defaults (360d, other)	-.2738		-.6811	1.052		.7838
	(-0.17)		(-0.44)	(0.38)		(0.28)
Defaults (360d, same)		.0028	.0379		.6019	.6311
		(0.01)	(0.17)		(1.48)	(1.59)
Specialization × Defaults (360d, same)		4.245***	4.631**		5.445	4.48
		(4.23)	(2.73)		(1.32)	(1.02)
Specialization	-4.101	-5.828	-4.582	-17.78	-16.6	-18.04
	(-0.78)	(-1.15)	(-0.86)	(-1.07)	(-1.13)	(-1.08)
Adj. R^2	.238	.238	.238	.474	.474	.474
N. Banks	29	29	29	31	31	31
Observations	4472	4472	4472	8933	8933	8933
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 11. Robustness: The Effect of Bank Specialization on Loan Contract Terms, dropping Loan-Level Controls

	CONTRACT STRICTNESS			ALL-IN DRAWN SPREAD			ALL-IN UNDRAWN SPREAD		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Specialization	-9.424**	-8.164**	-8.446**	-19.98**	4.058	-1.069	.59	3.768	3.647
	(-2.35)	(-2.19)	(-2.24)	(-2.04)	(0.37)	(-0.11)	(0.21)	(1.13)	(1.13)
Borrower Z-Score	-4.625***	-3.24***	-3.238***	-16.37***	-8.617***	-8.681***	-2.216***	-1.201***	-1.199***
	(-13.89)	(-5.05)	(-5.06)	(-9.31)	(-5.43)	(-5.45)	(-8.64)	(-3.49)	(-3.42)
Debt/Tang. Net Worth	-.0258	-.0188	-.0167	-.0894**	-.0294	-.0312	-.0144	-.0286***	-.0264***
	(-1.26)	(-0.48)	(-0.43)	(-2.15)	(-0.80)	(-1.10)	(-1.52)	(-4.15)	(-3.71)
Tang. Net Worth/Assets	-2.247	-9.696	-9.857	-39.02***	-34.69***	-31.38***	8.353***	6.113**	5.79**
	(-0.65)	(-1.50)	(-1.51)	(-4.27)	(-3.44)	(-2.92)	(5.71)	(2.55)	(2.50)
Current Ratio	1.097*	-2.298*	-2.315*	14.59***	-.9662	-1.838	1.553**	-1.683	-1.628
	(1.70)	(-1.69)	(-1.72)	(5.12)	(-0.57)	(-0.97)	(2.49)	(-1.10)	(-1.09)
Bank-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Rating FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Loan Type FE	No	No	Yes	No	No	Yes	No	No	Yes
Adj. R^2	.133	.526	.527	.346	.658	.68	.222	.547	.558
N. Banks	36	35	35	35	34	34	35	33	33
Observations	5500	4756	4756	5291	4558	4558	4529	3815	3815

This table reports the estimates of the coefficients from the following regression over our baseline sample, which includes only loans for which the contract strictness measure is available:

$$\textit{Loan Contract Term}_{f,b,t} = \alpha + \theta_{b,t} + \textit{Fixed Effects} + \beta \cdot \textit{Specialization}_{f,b,t-1} + \beta_F \cdot \textit{Firm Controls}_{f,t} + \varepsilon_{f,b,t}$$

in which *Loan Contract Term*$_{f,b,t}$ is either CONTRACT STRICTNESS (columns 1 to 3), ALL-IN DRAWN SPREAD (columns 4 to 6), and ALL-IN UNDRAWN SPREAD (columns 7 to 9) for a loan originated in time t by bank b to firm f. α is the common intercept, $\theta_{b,t}$ represents bank×time fixed effects, and *Fixed Effects* include, depending on the specification, firm fixed effects, rating (time-varying) fixed effects and/or loan type fixed effects . *Specialization* is a lagged 3-year rolling average of specialization dummy for bank b in the sector of firm f. Firm controls include the z-score, current ratio, the ratio of tangible net worth over total assets, and the ratio of debt over tangible net worth. In parentheses, t statistics obtained from clustering at the bank level. ***, **, * indicate statistical significance at the 1%, 5% and 10%, respectively.

Table 12. Robustness: The Effect of Bank Specialization on Loan Contract Terms with Different Averages of the Specialization Dummy

	CONTRACT STRICTNESS			ALL-IN DRAWN SPREAD			ALL-IN UNDRAWN SPREAD		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Specialization (1Y)	-5.78*	-2.271	-2.244	-11.99	12.39	9.623	2.127	4.249*	4.148
	(-1.75)	(-0.53)	(-0.52)	(-1.32)	(1.06)	(0.93)	(1.02)	(1.70)	(1.67)
Specialization (2Y)	-6.248*	-4.356	-4.333	-15.44	-2.725	-6.019	2.091	2.266	2.03
	(-1.78)	(-0.92)	(-0.91)	(-1.55)	(-0.24)	(-0.61)	(0.83)	(0.74)	(0.67)
Specialization	-7.477**	-8.319**	-8.34**	-18.66**	-1.144	-5.319	2.022	3.944	3.652
	(-2.08)	(-2.17)	(-2.16)	(-2.10)	(-0.10)	(-0.52)	(0.69)	(1.19)	(1.12)
Specialization (4Y)	-7.168	-10.95***	-10.94***	-19.19*	-5.536	-8.339	1.434	3.746	3.393
	(-1.66)	(-2.87)	(-2.82)	(-1.99)	(-0.47)	(-0.77)	(0.41)	(0.99)	(0.91)
Specialization (5Y)	-9.592*	-9.823*	-10.13*	-14.38	2.178	-.2374	1.338	3.381	2.651
	(-1.97)	(-1.90)	(-1.97)	(-1.07)	(0.16)	(-0.02)	(0.37)	(0.86)	(0.69)
Bank-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Rating FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Loan Type FE	No	No	Yes	No	No	Yes	No	No	Yes

This table reports the estimates of the coefficients on the *Specialization* variable – averaged over different time horizons – from the following regression over our baseline sample, which includes only loans for which the contract strictness measure is available:

$$\textit{Loan Contract Term}_{f,b,t} = \alpha + \theta_{b,t} + \textit{Fixed Effects} + \beta \cdot \textit{Specialization}\ (n\mathrm{Y})_{f,b,t-1} + \beta_F \cdot \textit{Firm Controls}_{f,t} + \beta_L \cdot \textit{Loan Controls}_{f,b,t} + \varepsilon_{f,b,t}$$

in which $\textit{Loan Contract Term}_{f,b,t}$ is either CONTRACT STRICTNESS (columns 1 to 3), ALL-IN DRAWN SPREAD (columns 4 to 6), and ALL-IN UNDRAWN SPREAD (columns 7 to 9) for a loan originated in time t by bank b to firm f. α is the common intercept, $\theta_{b,t}$ represents bank×time fixed effects, and *Fixed Effects* include, depending on the specification, firm fixed effects, rating (time-varying) fixed effects and/or loan type fixed effects . *Specialization*(nY) is a lagged n-year rolling quarterly average of the specialization dummy for bank b in the sector of firm f. In our baseline analysis, *Specialization* is averaged over 3 years, and is the one without parentheses in this table (third row). Firm controls include the z-score, current ratio, the ratio of tangible net worth over total assets, and the ratio of debt over tangible net worth. Loan controls include logarithms of maturity, number of participants and of the deal amount, and they are included in the specification for each column. In parentheses, t statistics obtained from clustering at the bank level. ***, **, * indicate statistical significance at the 1%, 5% and 10%, respectively.

Table 13. Robustness: The Effect of Bank Specialization on Loan Contract Terms across Different Samples based on Number of Lead Arrangers

	CONTRACT STRICTNESS			ALL-IN DRAWN SPREAD			ALL-IN UNDRAWN SPREAD		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Loans with ≤ 10 Lead Arrangers (Baseline)									
Specialization	-7.477**	-8.319**	-8.34**	-18.66**	-1.144	-5.319	2.022	3.944	3.652
	(-2.08)	(-2.17)	(-2.16)	(-2.10)	(-0.10)	(-0.52)	(0.69)	(1.19)	(1.12)
Observations	5484	4740	4740	5283	4549	4549	4526	3810	3810
Loans with ≤ 5 Lead Arrangers									
Specialization	-10.16**	-9.843*	-9.949**	-24.16***	-5.969	-10.3	1.505	3.673	3.447
	(-2.51)	(-2.01)	(-2.05)	(-2.90)	(-0.47)	(-0.88)	(0.50)	(1.06)	(1.00)
Observations	5449	4709	4709	5254	4522	4522	4502	3785	3785
Loans with 1 Lead Arranger									
Specialization	-13.35**	-13.62**	-13.93**	-25.05*	-.3457	-6.529	-1.582	-4.584	-4.799
	(-2.65)	(-2.07)	(-2.16)	(-1.94)	(-0.02)	(-0.39)	(-0.70)	(-1.15)	(-1.23)
Observations	4949	4204	4204	4792	4053	4053	4109	3393	3393
Bank-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Rating FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Loan Type FE	No	No	Yes	No	No	Yes	No	No	Yes

This table reports the estimates of the coefficients on the *Specialization* variable from the following regression over three different samples, one that includes all loans with at most 10 lead arrangers – as identified by our procedure – one that includes all loans with at most 5 lead arrangers, and one that includes only loans with 1 lead arranges:

$$\textit{Loan Contract Term}_{f,b,t} = \alpha + \theta_{b,t} + \textit{Fixed Effects} + \beta \cdot \textit{Specialization}_{f,b,t-1} + \beta_F \cdot \textit{Firm Controls}_{f,t} + \beta_L \cdot \textit{Loan Controls}_{f,b,t} + \varepsilon_{f,b,t}$$

in which $\textit{Loan Contract Term}_{f,b,t}$ is either CONTRACT STRICTNESS (columns 1 to 3), ALL-IN DRAWN SPREAD (columns 4 to 6), and ALL-IN UNDRAWN SPREAD (columns 7 to 9) for a loan originated in time t by bank b to firm f. α is the common intercept, $\theta_{b,t}$ represents bank×time fixed effects, and *Fixed Effects* include, depending on the specification, firm fixed effects, rating (time-varying) fixed effects and/or loan type fixed effects . *Specialization* is a lagged 3-year rolling quarterly average of specialization dummy for bank b in the sector of firm f. Firm controls include the z-score, current ratio, the ratio of tangible net worth over total assets, and the ratio of debt over tangible net worth. Loan controls include logarithms of maturity, number of participants and of the deal amount, and they are included in the specification for each column. In parentheses, t statistics obtained from clustering at the bank level. ***, **, * indicate statistical significance at the 1%, 5% and 10%, respectively.

Table 14. Robustness: The Effect of Bank Specialization on Loan Contract Terms using Different Set of Firm-level Controls

	CONTRACT STRICTNESS			ALL-IN DRAWN SPREAD			ALL-IN UNDRAWN SPREAD		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Specialization	-5.729	-8.332**	-8.291**	-10.7	-2.045	-6.388	1.806	3.781	3.493
	(-1.44)	(-2.32)	(-2.29)	(-1.31)	(-0.18)	(-0.62)	(0.61)	(1.14)	(1.06)
Borrower Z-Score	-3.654***	-2.483***	-2.46***	-15.35***	-8.494***	-8.414***	-2.01***	-1.009**	-.9739**
	(-11.24)	(-4.31)	(-4.30)	(-7.30)	(-4.83)	(-4.99)	(-5.36)	(-2.42)	(-2.40)
Borrower Leverage	.2877***	.294***	.2983***	.8644***	.7037***	.6581***	-.02	-.046	-.0437
	(6.98)	(5.97)	(5.92)	(4.82)	(3.29)	(3.14)	(-0.60)	(-0.76)	(-0.75)
Log(Borrower Assets)	-5.353***	3.861	4.031	-26.18***	-18.87***	-19.01***	-.5294	.6701	.6554
	(-6.20)	(1.42)	(1.42)	(-10.11)	(-3.67)	(-4.06)	(-1.52)	(0.75)	(0.65)
Current Ratio	-.8615	-2.853**	-2.843**	5.955**	-1.758	-2.539	1.352**	-1.501	-1.471
	(-1.53)	(-2.49)	(-2.54)	(2.24)	(-0.91)	(-1.14)	(2.23)	(-0.96)	(-0.95)
Bank-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Rating FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Loan Type FE	No	No	Yes	No	No	Yes	No	No	Yes
Adj. R^2	.212	.531	.532	.452	.666	.686	.256	.556	.568
N. Banks	36	35	35	35	34	34	35	33	33
Observations	5484	4740	4740	5283	4549	4549	4526	3810	3810

This table reports the estimates of the coefficients from the following regression over our baseline sample, which includes only loans for which the contract strictness measure is available, using an alternative set of firm-level controls:

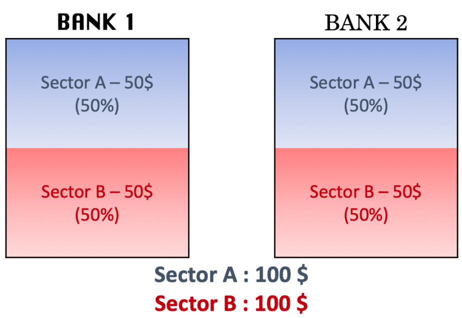
$$\textit{Loan Contract Term}_{f,b,t} = \alpha + \theta_{b,t} + \textit{Fixed Effects} + \beta \cdot \textit{Specialization}_{f,b,t-1} + \beta_F \cdot \textit{Firm Controls}_{f,t} + \beta_L \cdot \textit{Loan Controls}_{f,b,t} \varepsilon_{f,b,t}$$

in which $\textit{Loan Contract Term}_{f,b,t}$ is either CONTRACT STRICTNESS (columns 1 to 3), ALL-IN DRAWN SPREAD (columns 4 to 6), and ALL-IN UNDRAWN SPREAD (columns 7 to 9) for a loan originated in time t by bank b to firm f. α is the common intercept, $\theta_{b,t}$ represents bank×time fixed effects, and *Fixed Effects* include, depending on the specification, firm fixed effects, rating (time-varying) fixed effects and/or loan type fixed effects . *Specialization* is a lagged 3-year rolling average of specialization dummy for bank b in the sector of firm f. Firm controls include the z-score, current ratio, log of firm total assets, and firm leverage, measured as the ratio of total debt over total assets. Loan controls include logarithms of maturity, number of participants and of the deal amount, and they are included in the specification for each column. In parentheses, t statistics obtained from clustering at the bank level. ***, **, * indicate statistical significance at the 1%, 5% and 10%, respectively.

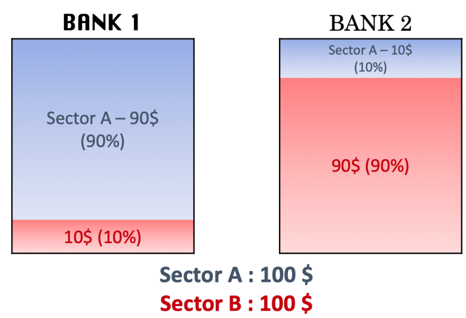
Appendix B. Figures

Figure 1. Understanding bank specialization

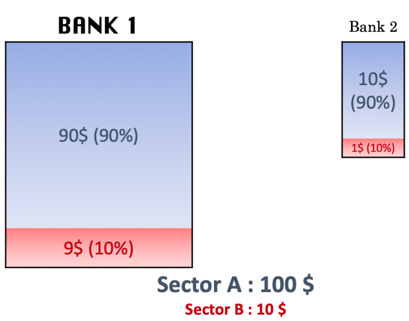
(a) Neither bank is specialized



(b) Both banks are specialized (1-A, 2-B)



(c) Neither bank is specialized



(d) Both banks are specialized (1-A, 2-B)

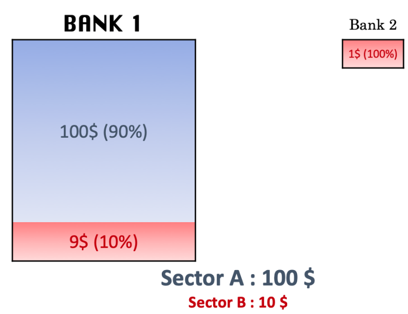
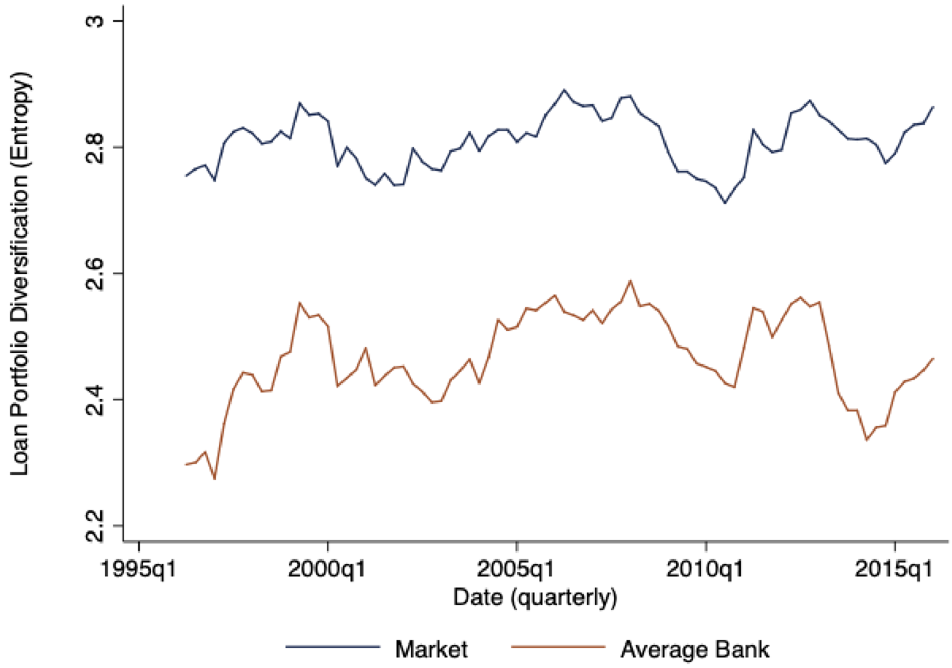
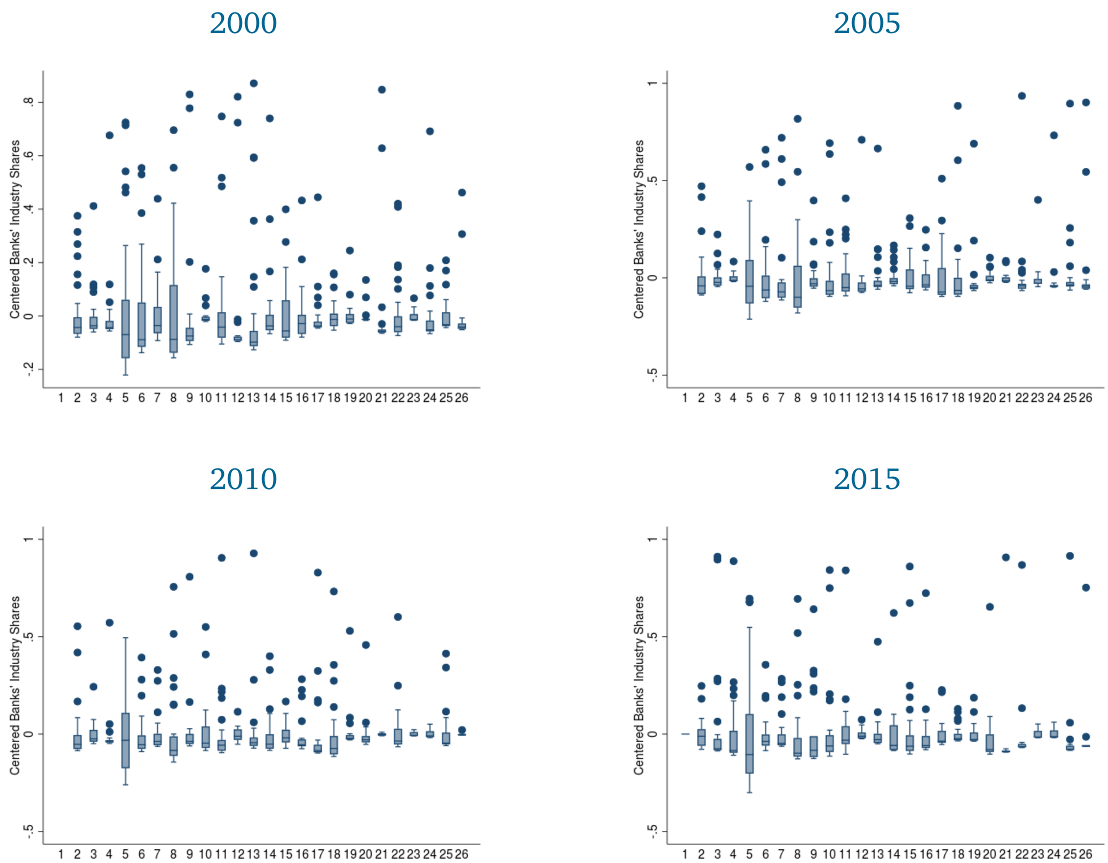


Figure 2. The average bank is less diversified than the market



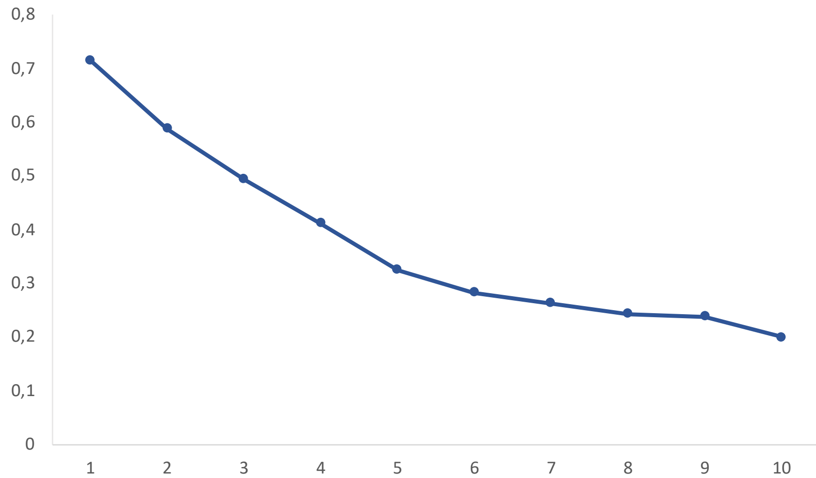
Note: **This figure plots the Market (Equation (2)) and Average Bank (Equation (3)) entropy measure of loan portfolio concentration over the TNIC industrial sectors.**

Figure 3. Specialization is common across industries and time



Note: This figure shows that "outlierness" is common among sectors and yearly cross-sections of our data. I.e., in every year, almost every sector has at least one outlier bank, which is exposed toward that sector considerably more than other banks do.

Figure 4. Specialization shows some persistence



Note: This figure plots the autocorrelation of the specialization (outlier) dummy over a ten year horizon.