Bank Specialization and the Design of Loan Contracts

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Abstract. We study bank specialization in lending in the US corporate loan market. We document that banks specialize in lending to specific industries. Specialization is persistent over time and common across industries. 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 financial covenants and no higher spreads. These results are not explained by relationship lending, high industry market shares, or geographical proximity, and are robust to using default shocks on lenders' loan portfolios as a source of variation in banks' self-assessment of screening abilities. Overall, our evidence suggests that banks specialize in lending because of information advantages in monitoring specific industries, and that the more generous contract terms offered by specialized banks could explain the limited degree of credit substitutability across specialized and non-specialized banks documented by recent literature.

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 & 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; bank specialization is common across industries and 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. To interpret this finding, we build on theoretical works such as Gârleanu and Zwiebel (2009), which argue

1. Berger and DeYoung (2001); Carey, Post, and Sharpe (1998); Hughes, Lang, Mester, and Moon (1996); Paravisini, Rappoport, and Schnabl (2017).
2. On the relation between bank portfolio concentration and related performances, see Acharya, Hasan, and Saunders (2006); Beck, Jonghe, and Mulier (2022); Boeve, Duellmann, and Pfingsten (2010); Hayden, Porath, and Westernhagen (2007); Tabak, Fazio, and Cajueiro (2011). On the real effects of bank specialization, see De Jonghe, Dewachter, Mulier, Ongena, and Schepens (2020); Gopal (2019); Paravisini et al. (2017); Schwert (2018).
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 a lower loan spread.
4. U.S. syndicated lending topples records in 2017, Reuters, December 2017.

that covenant strictness reflects the degree of information frictions between borrowers and lenders. In this sense, we suggest that the evidence we bring supports an explanation of bank specialization based on information advantages in screening and monitoring specific type of projects.

In order to perform our analysis, we obtain data on the 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. (2017) 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. Furthermore, specialization is persistent: a bank that is specialized in a given year has a 25% 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 covenant 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 the All-In Drawn Spread (AISD).[7] Looking at both is important as these contract terms are jointly determined, and there

5. We choose this sample period because coverage of the syndicated loan market sharply improves in DealScan after 1995 (Chava & Roberts, 2008).
6. This measure is similar to the one developed by Murfin (2012).
7. The AISD is a fee paid over the base rate (usually LIBOR) for each dollar of credit drawn.

might be a trade-off between them (Bradley & Roberts, 2015).

We find that the average loan contract between a bank specialized in a sector and a borrower from that sector includes covenants that are 24 percentage points less restrictive, and an all-in-drawn spread that is 30 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 covenant strictness it amounts to 60% of the empirical standard deviation; for the AISD, it amounts to 25% 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 expected default probability, size, leverage, liquidity, ability to provide collateral, profitability, age. 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 (Gârleanu & Zwiebel, 2009). 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 a higher spread 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 lower the cost of credit – consistent with the empirical results of Bharath, Dahiya, Saunders, and Srinivasan (2011) and Schenone (2010) – this appears to be uncorrelated with bank specialization. Moreover, we do not find any linear effect between relationship lending and covenant strictness.[8] 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 (2020) and Duquerroy, Mazet-Sonilhac, Mésonnier, and Paravisini (2022) for small business lending. Third, specialized banks might have high market share in an industry. Recent work by Giannetti and Saidi (2019) suggests 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.[9] We show that this is not the case, and find that banks with high market shares actually write contracts with similar covenant strictness and higher spreads, 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.

With this paper, we contribute to and connect two different strands of literature. First, to the literature focusing on various types of specialization in credit markets and their effects. For example, Carey et al. (1998) and Daniels and Ramirez (2008) highlight how different types of financial intermediaries – such as banks and private finance companies – specialize in lending

8. Prilmeier (2017) finds a non-linear, quadratic relationship between the intensity of the credit relationship and covenant strictness.

9. 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 (2014).

towards different types of firms. Black, Krainer, and Nichols (2020) show that in the commercial real estate mortgage market banks systematically fund riskier collateral compared to arm's length investors. Liberti, Sturgess, and Sutherland (2017) and Gopal (2019) document the role of lender specialization in collateral, and how this matters for lending decisions in new markets and in presence of lender constraints. Acharya et al. (2006), Beck et al. (2022), and Tabak et al. (2011), find that bank concentration has null or negative effects on bank risk.

Finally, Di and Pattison (2022), Duquerroy et al. (2022), De Jonghe et al. (2020), Jiang and Li (2022), and Paravisini et al. (2017) show that even within a single class of intermediaries, i.e. banks, there is specialization in lending towards specific firms, with positive effects on credit supply. Among these works, the closest ones are Jiang and Li (2022) and Paravisini et al. (2017). Both papers document the presence of a comparative advantage in lending, respectively towards specific industries and specific markets, focusing on the heterogeneity in credit supply responses to shocks by specialized and non-specialized banks. Overall, they suggest a degree of non-substitutability between credit provided by specialized banks and non-specialized banks.

We contribute in several ways. First, to the best of our knowledge, we are the first to look at the implications of lender specialization for financial contracting and security design. We show that bank specialization is an important determinant of both price and non-price terms, i.e. covenant strictness. Second, by leveraging detailed contract information, we provide a possible explanation of why credit obtained from specialized lenders is difficult to substitute: specialized lenders offer more generous terms that non-specialized lenders might not be able to offer. Third, we provide an alternative test to identify the presence of information advantages in lending associated with specialization, based on a measure of information distance between borrowers and lenders. Fourth, by documenting evidence of industry specialization in the US syndicated loan market, we complement the findings of the contemporaneous work by Jiang and Li (2022).

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. Abuzov, Herpfer, & Steri, 2020; Berlin & Mester, 1992; Billett, King, & Mauer, 2007; Bradley & Roberts, 2015; Demerjian, Owens, & Sokolowski, 2018; Demiroglu & James, 2010; Murfin, 2012), or pricing (e.g. Cai, Eidam, Saunders, & Steffen, 2018; Ivashina, 2009). Closer to our paper, a smaller set of studies stresses the importance of jointly taking into account borrowers and lenders characteristics when looking at the determinants of contract features. Prilmeier (2017) shows that bank-firm relationships affect covenant design. Hubbard, Kuttner, and Palia (2002) and Santos and Winton (2019) document that the interaction of bank capital and firm profitability matters for the determination of loan spreads. Bao (2019) finds that peer effects in loan portfolios affect the cost of credit. With respect to these studies, we provide an additional joint dimension—lender's industry specialization and borrower's industry—that is relevant for the determination of price and non-price terms.

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.[10] We also merge firm characteristics in Compustat with the industry classification

10. The linking table is constantly being updated, as of April 2022 this is the most recent and comprehensive version.

developed by Hoberg and Phillips (2010, 2016), which is available for most public companies present in Compustat starting from 1987.

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. 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.[11] 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).[12] We identify a lead arranger following the procedure outlined in Chakraborty et al. (2018).[13]

We restrict the sample to loans originated between 1996 to 2016, since the coverage of the syndicated lending activity and contract terms in Dealscan is sparse before 1996 (Chava & Roberts, 2008). We further restrict the sample to loans that have borrowers headquartered in the US. We also drop from our sample all loans to financial corporations (Compustat SIC codes from 6000 to 6999).[14] All variables, except the measures of covenant strictness and of expected default probability that are naturally bounded between 0 and 100, are winsorized at the 1st and 99th percentile.

11. See, for example, Chakraborty, Goldstein, and MacKinlay (2018); Prilmeier (2017); Schwert (2018).
12. If there are multiple lead arrangers, we split the loan amount equally among them.
13. 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, both are employed to define which bank has a lead role. Chakraborty et al. (2018), who in turn follow Bharath, Dahiya, Saunders, and Srinivasan (2007); Bharath et al. (2011), defines as lead arranger, within each syndicate, the bank that "scores" highest in the following ten-part raking: "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 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"." (Chakraborty et al. 2018, Online Appendix, p.1)
14. However, to compute the measures of specialization we retain every loans from 1987 to 2016 for which we can identify a borrower in Compustat and for which the TFIC classification is available, regardless of headquarter or SIC codes. Computing the measures of specialization from 1996 does not affect our results.

The unit of observation in DealScan is a loan facility. However, information on loan covenants is available only at the package, or deal, level. Since in our analysis the main dependent variable is covenant strictness, 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 concentrated the commercial lending portfolio of an average bank is relative to the whole syndicated-loan market portfolio. Intuitively, if banks are more concentrated than the market, it means at the very least that they prefer to focus 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.

In the first approach, we employ the Herfindahl-Hirschman Index (*HHI*), commonly used to measure the degree of market concentration. Specifically, we use it to characterize the level of concentration of the market portfolio and of the average bank, with respect to the different industries in the economy.[15] The *HHI* of the commercial lending portfolio of a given bank is defined as follows:

$$HHI_{b,t} = \sum_{i=1}^{I} L_{i,b,t}^2 \tag{1}$$

in which $L_{i,b,t}$ denotes the portfolio share of loans from bank b, towards industry i, at time t.

15. There are various ways to characterize portfolio concentration/diversification. See Avila, Flores, Lopez-Gallo, and Marquez (2013) for a comparison of the various approaches employed in banking and finance.

$HHI_{b,t}$ reaches its maximum – which is equal to 1 – in presence of a perfectly concentrated portfolio, i.e. $L_{i,b,t} = 1$ for only one industry i, and 0 for all the others, and its minimum – equal to $1/I$ in presence of a perfectly diversified portfolio, i.e. $L_{i,b,t} = 1/I \ \forall i \in I$.

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

$$\overline{HHI}_{b,t} = \sum_{b=1}^{B} \frac{L_{b,t}}{L_t} \left(\sum_{i=1}^{I} L_{i,b,t}^2 \right) \tag{2}$$

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

Similarly, we can define the *HHI* 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 *HHI* for the "market" portfolio as follows:

$$HHI_{M,t} = \sum_{i=1}^{I} L_{i,t}^2 \tag{3}$$

in which $L_{i,t} = \sum_{b=1}^{B} L_{i,b,t}$ 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. (2017) to capture bank specialization at the industry level. According Paravisini et al. (2017), 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 variable, defined as follows:

$$Spec_{i,b,t} = \begin{cases} 1 & \text{if } L_{i,b,t} \geq L_{it}^* \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

in which $L_{i,b,t}$ 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 times 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 may 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 on the amount of credit that goes from each bank to each sector. In fact, in panel (d), Bank 1 is specialized in sector A, and bank 2 is specialized in sector B. Bank 1 provides overall more credit to sector B than Bank 2, but its portfolio share is really small compared to Bank 2, which only lends to 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 this purpose we rely on DealScan, which allows us to obtain data on bank-firm credit relationships. The focus is on syndicated lending, which represents a sizable portion of the corporate loan market in the US. Since DealScan only provides information on loan originations, we create a panel akin to a credit registry by aggregating DealScan loan-level data at the bank-firm relationship level over time, similarly to Chakraborty et al. (2018) and Lin and Paravisini (2012).

We assume each loan is outstanding until the original end date, or, if the information is available on DealScan, until the amended end date.[16] 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 comparative advantage in lending towards specific types of projects in the economy, we use the Text-based Fixed Industry Classifications (TFIC) 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. Specifically, TFIC uses textual data to track the products (types of projects) that characterize each firm's core business activity. Then, it classifies firms as belonging to a specific cluster (industry) based on the similarity of the firm's core activity. This classification follows the evolution of the firm's core business over time, and thus it is closer in spirit to what we aim to measure than a static NAICS or SIC industry definition.

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 TFIC classification, from 1987 to 2016.

First, we look at the measure of loan portfolio diversification. In Figure 2, we plot the *HHI* of the commercial lending portfolio for the average bank computed for each quarter as in **??**, and the same measure computed for the market portfolio as in Equation (3). Given that a larger value of this measure imply larger concentration of exposure, a comparison of the two reveals that the loan portfolio of the average bank is more concentrated than the market. Comparing the average *HHI* of the market portfolio(~ 0.7) and that of the average bank (~ 0.105) over time, we see that the average bank is significantly more concentrated than the market. This

16. To track loan amendments, we exploit the information present in the "facilityamendment" table present in the legacy version of Dealscan in WRDS. One potential caveat is that renegotiated/amended loans could appear as new loans in DealScan; if loan renegotiations are not identically and independently distributed across bank-firm pairs, this could imply an imperfect measurement of a bank's lending activity. To partially address this issue, we perform our analysis dropping from our sample all the loans that have a description such as "This loans amends and restates..." in the various "comment" fields available in Dealscan. All the results of the paper are robust to not dropping these loans.

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. Specifically, we are interested in understanding whether we can observe abnormally large loan portfolio shares towards certain industries, similarly to what Paravisini et al. (2017) do for countries of destination for Peruvian exporting firms. Figure 3 shows, at four different moments in time, the box-and-whisker plots of the distribution of $L_{it}^{b} - \bar{L}_{it}$, that is of bank portfolio shares towards each industry i demeaned by the average share of lending in that industry. We can see that across time almost every industry display at least one or more right-tail outliers; that is, one or more specialized lenders. Moreover, specialization is persistent. In Figure 4 we plot the autocorrelation of $Spec_{it}^{b}$ defined in Equation (4), and we can see that a bank specialized in lending towards an industry in a given year is 25% 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 bank specialization in lending as a defining feature of the US syndicated loan market.

2.3. Measurement of Economic Variables

2.3.1. Dependent Variables: Loan Covenant Strictness and Loan Spreads

Our goal is to understand whether specialization is associated with 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 Gârleanu and Zwiebel (2009), 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, when a contract includes more than one covenant it is not obvious how to assess the overall strictness of the covenant package. Therefore, we are going to rely on the measure of covenant strictness developed and made available by Demerjian and Owens (2016).[17]

Covenant 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, since there is a trade-off between covenants and the cost of credit—stricter contracts might be associated with lower costs and viceversa (Bradley & Roberts, 2015; Matvos, 2013; Reisel, 2014). Therefore we also collect information on loan pricing available on DealScan, in particular we focus on the All-in Drawn Spread (AISD) 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.

2.3.2. 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' industry market share.

We create different proxies to capture the strength of a bank-firm credit relationship. Specifically, we define four measures, following Bharath et al. (2007, 2011); Prilmeier (2017); Schenone (2010). *Previous Rel.*$_{f,b,t}$ captures the presence of an existing credit relationship between firm f and bank b at the extensive margin. It is a dummy variable that takes value 1 if bank b granted a loan to firm f in the 3 years prior to a loan at time t. *Rel. Intensity (Amt)*$_{f,b,t}$ and *Rel. Intensity (Num)*$_{f,b,t}$ capture the strength of the credit relationship at the intensive

17. The measure developed by Demerjian and Owens (2016) can be downloaded on Edward L. Owens' personal website https://sites.google.com/site/edowensphd/researchdata. We thank Demerjian and Owens (2016) for making the measure available.

margin. They are defined, respectively, as the fraction of credit (loans) that firm f obtained from bank b over the total amount of credit (number of loans) firm f took out over the 3 years prior to a loan at time t. Finally, we compute the length of an outstanding bank-firm relationship. *Rel. Length*$_{f,b,t}$ is defined as the time elapsed between period t and the first interaction between firm f and bank b in DealScan.

We also collect information on the geographic distance between the borrower and the lender, to proxy for "arms-length" credit relationships. In particular, we construct a dummy variable, *Same State*$_{f,b,t}$, which takes value 1 if bank b and firm f are in the same state at time t, and 0 otherwise.[18] 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 (2019) show 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. All other variables are defined in Table 1.

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 obtained from the sample selection procedure described in Section 2.1. The second one, "Strictness Sample", is the subsample of loans for which both the All-In Drawn Spread and covenant strictness measure developed by Demerjian and Owens (2016) are non-missing. We conduct our main empirical analysis over this subsample.

The top panel of Table 2 reports information on the characteristics of loan-level variables in our samples. The Strictness Sample includes 11,684 distinct loans. On average, a loan agreement contains more than two financial covenants, displays a level of strictness such that the borrower has 36% probability to violate at least one of the covenants and a All-In-Drawn Spread of 188 basis points. The average loan package has maturity of almost 4 years, amounts

18. We use the historical data on firm and bank locations collected from the SEC filings by Bai, Fairhurst, and Serfling (2020) and Gao, Leung, and Qiu (2021), supplementing them with Compustat header information when missing.

to \$567 million, and the average syndicate size (number of lenders) is 9. These statistics are similar to the larger Matched sample, which displays on average 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 11,231 firm-quarter observations for 3,634 firms. These are public firms, large – on average \$1 billion in total assets – and mature – on average 20 years since IPO. 55% do not have a long-term issuer credit rating, and for those that have a rating, the average rating is BBB-/BB+.[19] Over our sample period (1996-2016), they enter, on average, into 9 syndicated loan agreements. Overall, there are no major differences between the Strictness and the Matched Sample.

Finally, the bottom panel of Table 2 reports information on the lenders in our samples. The Strictness Sample includes 2,093 bank-quarter observations for 95 banks. The average bank is large, with \$200 billion in total assets, a deposit to asset ratio of 60%, with book equity capital amounting to 7%.

3. Bank Specialization and Loan Contract Terms

In this section we explore the effect of bank specialization in lending on loan covenant 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. Employing different multivariate specifications aimed at mitigating this concern, we then show that bank specialization is associated with significantly lower covenant 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 own 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, further substantiating our interpretation.

19. Rating is a categorical variable. We assign value 1 to AAA ratings, 2 to AA, and so on. The largest value is 9, assigned to "D" or "SD" indicating default in the Capital IQ Long-Term Issuer 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.

Loans arranged by specialized banks in their industries of specialization display several different features compared to loans arranged to other industries and/or non-specialized banks, even though they are similar in their amount. In particular, "specialized loans" display stricter covenants, higher spreads, shorter maturities, a more concentrated syndicate, and a lower fraction of revolving credit, compared to"non-specialized loans". Even though this is suggestive of a relationship between bank specialization and contract features, this evidence may simply arise from the different characteristics of specialized banks and their borrowers. By performing t-tests on bank and firm characteristics, we aim to understand whether this is the case.

The mid panel of Table 3 displays the results of the t-tests for firm characteristics.[20] The estimates confirm that firms obtaining loans from banks specialized in the industry they belong to are generally different from other firms. They are smaller, younger, less likely to have a long-term issuer credit rating – even though if they do have a credit rating, it is on average similar to other firms. This implies that a firm borrowing from banks specialized in its own industry is less likely to to have access to public debt/equity markets and thus subject to more severe information frictions. These firms also appear to perform slightly better in terms of liquidity, tangibility, and leverage.

The bottom panel of Table 3 shows the estimate of t-tests on bank characteristics.[21] 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 towards a given sector are different compared to other banks. Specifically, they are smaller, have a larger reliance on deposits, they appear to be better capitalized, and more profitable,

20. We split all firm-quarter observations into those that are associated with a loan arranged to any sector any bank is specialized in, and those that are not. We do the same for bank-quarter observations.

21. 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.

with a similar ratio 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 covenant 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 covenant strictness might just be the direct consequence of the systematically different characteristics of the firms and banks involved.[22]

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-quarter*, 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 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.[23]

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

23. Ideally, we would rather to have a within bank-time and within firm-time specification. Unfortunately, as we

Formally, we employ the following specification:

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

in which *Loan Contract Term*$_{f,b,t}$ stands for loan covenant strictness or the all-in-drawn spread for a loan originated in quarter t by bank b to firm f. $\theta_{b,y(t)}$ 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 $Spec^b_{it}$ (defined in Equation (4)). *Firm Controls* includes firm level proxies of time-varying risk. Specifically, it includes the expected default probability (EDF), based on the Merton model of credit risk (Merton, 1974) and computed implementing the "naive" approach proposed by Bharath and Shumway (2008), as well as log of total assets, debt to asset ratio, current ratio, tangible net worth to asset ratio, interest coverage ratio, and years since IPO. These controls account for repayment risk (especially for non-rated firms), size, leverage, liquidity, the ability to provide collateral, firm profitability, and firm age.[24] Finally, *Loan Controls* includes also loan-level controls such as log of maturity, log of loan amount, log of number of syndicate participants, the fraction of revolving credit over the total package amount, and separate intercepts for different loan purposes.

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 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.[25]

work on a sample of very large loans, we do not see the many firms doing multiple deals in the same year-quarter. This makes the adoption of such strategy infeasible.

24. Similar controls are used in similar studies focusing on loan covenant strictness, such as Murfin (2012) or Prilmeier (2017).

25. 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—see the robustness checks presented in Section 3.6. Finally, we note that the same choice of rolling window length, performed for similar reason, can also be found in Paravisini et al. (2017).

3.3. The Effect of Specialization on Loan Covenant 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 two of the main different loan contract characteristics: Covenant Strictness and the All-In Drawn Spread (AISD). Looking at covenant 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 AISD are also negative across specifications.

In particular, a simple regression of covenant strictness on bank-time fixed effects shows that a loan contract with a firm in the bank's area of specialization display less strict covenants by 12.4 percentage points compared to firms in other industries (column 1). This estimate is economically significant, as it amounts to 33% of the mean value and 30% of the standard deviation of the distribution of covenant strictness in our sample. Note that this is not associated with higher loan spreads: the point estimate on the specialization variable in relation to the AISD is negative (column 4).

When we account for borrower selection and borrower risk by including firm fixed effects and firm controls, the results are even stronger. The point estimate of the coefficient on bank specialization doubles for both covenant strictness and AISD. Banks specialized in an industry provide credit to firms in that industry with covenants looser by 24 p.p. relative to firms in other industries, with no higher cost of credit (columns 2 and 5). Alternatively, a 1 standard deviation increase in bank specialization implies a decrease in covenant strictness by 4 p.p. These results reduce concerns that the effect of specialization is entirely a byproduct of unobserved heterogeneity in borrower types and riskiness.

However, banks specializing in lending towards certain industries might provide credit with characteristics 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 non-specialized banks only in the form of revolving credit. To address this concern we include loan controls to the baseline specification, and as shown in columns 3 and 6, results are virtually unchanged, while the effect on AISD becomes slightly larger and marginally statistically significant.

The negative, economically and statistically significant effect of the specialization variable on covenant strictness suggests less information asymmetry, or “distance”, between a bank specialized in lending towards a given industry and firms in that industry, in line with the theoretical framework developed by Gârleanu and Zwiebel (2009). The negative estimates on the same specialization variable when loan spreads are the dependent variables support this interpretation, 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 as a risk for which they must be properly compensated. This suggests less restrictive covenants actually reflect better ex-ante knowledge of the projects/capacity to screen them, and this is consistent with explanations of bank specialization based on the existence of lending advantages, specifically an industry-specific information advantage.

3.4. Assessing Alternative Explanations

There might be alternative explanations for the results presented in Table 4. In particular, the results presented so far are consistent with at least three other economic mechanisms: presence of borrower-specific knowledge (relationship lending), insurance incentives stemming from a high industry market shares, and local knowledge spillovers implied by geographical, rather than industry, specialization.

Relationship Lending

First, we could argue that the industry-specific information advantage could originate from an information advantage that is borrower-specific. This would be consistent with widespread“relationship lending” (Berger & Udell, 1995; Petersen & Rajan, 1994, 1995). For example, Bharath et al. (2011) and 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 covenant strictness, we include in our specification the various empirical proxies we described in Section 2, which are meant to capture different aspects of relationship lending. Table 5 reports the results for these regressions. Across all specifications, for both covenant strictness and loan spreads, the estimated coefficient on the specialization variable is virtually unchanged and still statistically significant, validating the hypothesis that banks have an information advantage that stems from an industry-specific expertise and not only from borrower-specific information.

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

High Industry Market Share

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 industry market share. The literature points out that this could be an alternative mechanism explaining our findings. Giannetti and Saidi (2019) show that banks with 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 related 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 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 6 reports the results for these regressions. When looking at covenant strictness, the estimates on the specialization variable are slightly larger and still highly significant. For loan spreads, we still observe negative result of the specialization variable, confirming the results of the main analysis.

Turning to the effect of a high market share, we can see that the estimated coefficient for the market share variable on covenant strictness is not significant (columns 1-3), wheres it is positive and significant on AISD (columns 5 and 6). 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 higher loan spreads. 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 & Hauswald, 2010; Alessandrini, Presbitero, & Zazzaro, 2008; Degryse & Ongena, 2005), even in market of large corporations (Hollander & 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 based on 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 7 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 covenant strictness and loan spreads. However, they are not significant. On the other hand, the estimated coefficients on the specialization variable are essentially the same as the baseline specifications.

3.5. Specialization and Defaults on Lender Portfolios

To provide further evidence in support of our proposed interpretation, we employ defaults on lender loan portfolios as a relatively exogenous source of variation to the lenders' perception of their own screening ability (Murfin, 2012). We examine whether defaults of firms in industry i that have outstanding loans with bank b differentially affect the contracting behavior of banks that are specialized in lending to i and banks that are not. In particular, we focus on how covenant strictness changes for loans underwritten by specialized and non-specialized banks following the default shocks.

We compute the number of defaults each bank experiences in its loan portfolio by counting instances in which borrowers with an outstanding loan with a given bank have a credit rating of "D" or "SD" over a period 90 days, following Murfin (2012). Suppose that banks specialized in lending towards one sector have an information advantage in screening or monitoring specific projects in that sector. We posit that, for a given number of borrowers in a industry defaulting while having outstanding loans with a bank, 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. Indeed, 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 observe a smaller or null 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:

$$\begin{aligned} Loan\ Term_{f,b,t} = {} & \theta_{b,t} + \theta_f + \rho \cdot Specialization_{f,b,t-1} \times Defaults_{b,t-1} \\ & + \beta \cdot Specialization_{f,b,t-1} + \gamma_D \cdot Defaults_{b,t-1} + \gamma \cdot X_{f,b,t} + \varepsilon_{f,b,t} \end{aligned} \tag{6}$$

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 in making covenants stricter– 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 other industries.

Table 8 shows the results of regressions as in Equation (6), and the evidence is consistent with our hypotheses. From this table we can observe that the coefficient on the specialization variable is very similar to the baseline regression, and still highly significant. Two patterns also emerge. When specialized banks incur defaults in their loan portfolios, they increase covenant strictness relatively more than non-specialized banks, but only when these defaults occur to borrowers in the industry the bank specializes in. When defaults occur outside of the industry of specialization of the bank, there is no differential response in terms of covenant strictness. In fact, the coefficient on the interaction term between the specialization variable and the number of defaults is positive and highly statistically significant only when the defaults occur in the industry of specialization of the bank

In terms of economic interpretation of the coefficients, a specialized bank in an industry that suffers from one default in a quarter, and this default concerns a borrower in its industry of specialization, will respond by increasing covenant strictness by approximately 30 p.p. relative to a specialized bank that does not experience default, and by approximately 6 p.p $(-24.36 + 30.28 \times 1)$ relative to a non-specialized bank that suffer from 1 default in the same industry.

3.6. Robustness Checks

The results presented so far stand to a series of robustness checks. First, restricting the analysis only to loans with a single lead arranger confirms the baseline results, as shown in

Table 9. Second, computing the specialization measures starting from 1996 instead of 1987 leaves the results virtually unchanged; the estimates are presented in Table 10. Third, repeating the analysis focusing on the pre-2008 sample period also confirms the main results, and if anything the estimates are even stronger, as displayed in Table 11. This alleviates concerns that our results are driven by the post-financial crisis period, in which the share of leveraged, cov-lite loans increased dramatically and relatedly the coverage of covenants offered by Dealscan appears to have decreased in quality (Bräuning, Ivashina, & Ozdagli, 2021).

Finally, averaging the specialization dummy defined in Equation (5) over different time horizons does not change the main message of the paper. As can be seen in Table 12, the effect of the specialization variable on covenant strictness is very similar in both economic magnitude and statistical significance when averaging over 3, 4 or 5 years, in particular for covenant strictness (columns 3, 4 and 5). The estimate of specialization on covenant strictness is attenuated both economically and statistically when averaging over 4 or 8 quarters (1 or 2 years), but on the other hand it is larger and statistically significant when looking at the AISD. The lower and mostly non-statistically significant estimates that we obtain when averaging the specialization dummy over a period of 1 and 2 year could actually represent an indirect validation of our proposed mechanism. It takes time to build expertise that is industry-specific, and therefore estimates on covenant strictness are larger and less noisy once the average of the specialization dummy is taken over longer periods.

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-quarter, one towards the industry of specialization and one to any other industry. Our results cannot be fully explained by borrower risk, relationship lending, a high industry market share, or geographical proximity.

We look at our results in light of financial contracting theory, and interpret the restrictiveness of the covenant structure as the degree of information asymmetry between a borrower and a lender (Gârleanu & Zwiebel, 2009). Thus, we conclude that specialized banks have a comparative advantage in monitoring specific industries. 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 (see Corbae & D'Erasmo, 2021). Moreover, documenting implications on the non-price conditions of credit, we propose a possible mechanism which makes credit by specialized banks difficult to substitute (Paravisini et al., 2017).

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Appendix A. Tables

Table 1. Variable Definition

Variable Name	Definition	Data Source
Specialization	Rolling 12-qtr sum of specialization dummy, as defined in Equation (4)	Dealscan
Specialization (nY)	Rolling 4n-qtr sum of specialization dummy, as defined in Equation (4)	Dealscan
EDF	See Bharath and Shumway (2008), pp. 1247-48	CRSP/Compustat
Assets	`atq`	Compustat
Tangibility	`(atq - intanq - ltq)/atq`	Compustat
Leverage	`(dlttq + dlcq)/atq`	Compustat
Current Ratio	`actq/lctq`	Compustat
Ln(1+Int. Cover. Ratio)	Ln(1 + rolling 4-qtr sum of `oibdq`/rolling 4-qtr sum of `xintq`)	Compustat
Years since IPO	Current date minus first date in Compustat	Compustat
Rated	Dummy variable equal to 1 if firm-quarter has a long-term issuer credit rating, 0 otherwise	Capital IQ
Rating	Categorical variable equal to 1 for credit rating "AAA", to 2 for "AA", ... , to 9 for "D"/"SD"	Capital IQ
N. Loans	Number of packages per borrower over sample period	Dealscan
Covenant Strictness	Ex-ante prob of violating one financial covenant. See Demerjian and Owens (2016)	Ed. Owens' site
N. Covenants	Number of financial covenants in package	Dealscan
All-In Drawn Spread	Average of each facility's `allindrawn` in package weighted by `facilityamt`	Dealscan
All-In Undrawn Spread	Average of each facility's `allinundrawn` in package weighted by `facilityamt`	Dealscan
Ln(Loan Amount)	Ln(`dealamount`)	Dealscan
Ln(Maturity)	Ln(average of each facility's `maturity` in package weighted by `facilityamt`)	Dealscan
Ln(Lenders)	Ln(N. syndicate members)	Dealscan
Revolver Fraction	Revolver credit amount in package / `dealamount`	Dealscan
Previous Rel.	Described in Section 2.3.2	Dealscan
Rel. Intensity (Amt)	Described in Section 2.3.2	Dealscan
Rel. Intensity (Num)	Described in Section 2.3.2	Dealscan
Rel. Length	Described in Section 2.3.2	Dealscan
Market Share	Described in Section 2.3.2	Dealscan
Same State	Described in Section 2.3.2	Compustat/SEC
Defaults	N. outstanding loans to firms with cred. rat. changed to "D"/"SD" over prev. qtr	Dealscan/Capital IQ

Table 2. Descriptive Statistics

This table reports the descriptive statistics for the full matched Dealscan-Compustat sample obtained after applying the selection criteria described in Section 2.1, and for the Strictness sample, which further restricts the sample to observations with non-missing covenant strictness and all-in drawn spread. Loan and firm characteristics are described in Table 1. Bank characteristics are taken from Compustat NA/Compustat Bank, and are defined as follows. *Ln(Assets)* is the natural logarithm of bank total assets (`atq`), in $M. *Deposits* is the ratio of total deposits (`dptcq`) to total assets, in %. *Book Equity* is the ratio of bank book equity (`ceqq`) to total assets, in %. *Market Equity* is the ratio of market capitalization (`prccq`×`cshoq`) to total assets minus book equity plus market capitalization, in %. *Tier 1 Capital* is the ratio of bank core equity to risk-weighted assets (`capr1q`), in %. *Non-Performing Assets* is the ratio of non-performing assets(`npatq`) to total assets, in %. *Profitability* is the ratio of net income (`niq`) to total assets, in %.

	Matched Sample			Strictness Sample		
	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.
Loan Characteristics						
Covenant Strictness	35.86	41.19	12,124	35.85	41.17	11,684
N. Covenants	2.46	1.13	14,483	2.47	1.14	11,684
All-In Drawn Spread	190.93	128.36	22,724	188.22	118.43	11,684
All-In Undrawn Spread	30.25	19.07	16,618	31.67	18.59	9,923
Loan Amount ($M)	620.64	1,444.92	23,164	567.59	1,201.17	11,684
Maturity (Months)	45.45	22.25	22,266	46.02	19.99	11,628
N. Lenders	7.98	8.72	23,164	9.04	9.36	11,684
Revolver Fraction	0.74	0.38	23,164	0.79	0.34	11,684
Previous Rel.	0.69	0.46	18,167	0.70	0.46	9,127
Firm Characteristics						
Ln(Assets)	7.02	1.92	21,416	6.80	1.82	11,231
EDF	0.05	0.17	19,275	0.06	0.17	10,209
Tangibility	0.20	0.30	13,857	0.20	0.29	7,200
Leverage	0.30	0.21	20,656	0.31	0.20	10,879
Current Ratio	1.91	1.25	20,626	1.87	1.15	10,885
Ln(1+Int. Cover. Ratio)	2.23	1.14	16,432	2.20	1.05	8,999
Years since IPO	20.18	16.79	20,732	19.62	16.11	10,932
Rated	0.46	0.50	21,417	0.45	0.50	11,231
Rating	4.50	1.18	9,829	4.62	1.05	5,064
N. Loans	9.03	6.89	21,417	8.81	6.41	11,231
Bank Characteristics						
Ln(Assets)	12.39	1.58	2,723	12.39	1.57	2,093
Deposits	61.93	12.84	2,069	61.47	12.66	1,651
Book Equity	7.26	2.89	2,673	7.35	2.75	2,062
Market Equity	12.10	6.52	2,503	12.58	6.52	1,944
Tier 1 Capital	9.71	2.17	1,935	9.50	2.13	1,574
Non-Performing Assets	0.65	0.52	1,754	0.63	0.49	1,441
Profitability	0.25	0.17	2,072	0.26	0.18	1,654

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

This table reports the results of a battery of univariate t-test, meant to document systematic differences in loan, firm and bank-level observables between loans made by a specialized bank within its sector of specialization and out of its sector of specialization. For each observable X listed in the table, H_0 is that $E[X(\mathit{Specialized}) - X(\mathit{Non\text{-}Specialized})] = 0$.

	Spec.	Non Spec.	Diff.	t-Stat	N (Spec.)	N (Non Spec.)
Loan Characteristics						
Covenant Strictness	40.23	35.06	5.17	3.30	733	11,484
N. Covenants	2.53	2.44	0.09	2.44	938	13,616
All-In Drawn Spread	231.28	189.62	41.66	11.72	1,416	21,813
All-In Undrawn Spread	32.45	30.12	2.32	3.53	904	15,931
Loan Amount ($M)	666.63	668.65	−2.03	−0.05	1,448	22,237
Maturity (Months)	40.35	46.16	−5.80	−9.34	1,391	21,394
N. Lenders	6.25	8.24	−1.99	−8.38	1,448	22,237
Revolver Fraction	0.69	0.74	−0.04	−4.11	1,448	22,237
Previus Rel.	0.67	0.68	−0.02	−1.15	1,028	17,668
Firm Characteristics						
Ln(Assets)	6.37	7.24	−0.88	−16.65	1,448	22,236
EDF	0.07	0.05	0.02	3.24	1,266	20,107
Tangibility	0.21	0.19	0.03	2.56	833	14,856
Leverage	0.28	0.31	−0.03	−5.14	1,372	21,505
Current Ratio	2.23	1.85	0.38	11.13	1,403	21,397
Ln(1+Int. Cover. Ratio)	2.19	2.21	−0.02	−0.64	888	17,452
Years since IPO	16.88	21.09	−4.21	−8.92	1,404	21,512
Rated	0.36	0.49	−0.13	−9.61	1,448	22,237
Rating	4.58	4.49	0.09	1.75	524	10,938
Bank Characteristics						
Ln(Assets)	11.3	13.3	−1.96	−3.33	1,375	21,548
Deposits	68.1	55.3	12.7	3.13	1,105	18,391
Book Equity	8.10	7.65	0.45	1.01	1,352	21,357
Market Equity	14.9	12.1	2.83	2.44	1,268	20,743
Tier 1 Capital	10.0	9.36	0.69	0.92	1,059	18,005
Non-Performing Asset	0.63	0.62	0.012	0.15	997	17,151
Profitability	0.29	0.25	0.039	2.29	1,104	18,351

Table 4. The effect of bank specialization on covenant strictness and loan spread

This table reports the estimates of the coefficients from the following regression over our baseline sample, which includes loans for which the loan covenant strictness and all-in drawn spread are available:

$$\text{Loan Term}_{f,b,t} = \alpha + \theta_{b,t} + FEs + \beta \cdot \text{Specialization}_{f,b,t-1} + \gamma \cdot X_{f,b,t} + \varepsilon_{f,b,t}$$

in which *Loan Term*$_{f,b,t}$ is either the covenant strictness (columns 1 to 3) or the all-in drawn spread (columns 4 to 6) for a loan originated in year-quarter t by bank b to firm f. α is the common intercept, $\theta_{b,t}$ represents bank×year-quarter fixed effects, and*FEs* include, depending on the specification, firm fixed effects, firm rating fixed effects, loan purpose fixed effects. $X_{f,b,t}$ represents firm and loan controls. All the variables are defined in Table 1. In parentheses, t statistics obtained from two-way clustering at the bank and borrower level. ***, **, * indicate statistical significance at the 1%, 5% and 10%, respectively.

	Covenant Strictness			All-In Drawn Spread		
	(1)	(2)	(3)	(4)	(5)	(6)
Specialization	−12.4**	−23.56***	−24.35***	−14.19	−28.45	−31.77*
	(−2.51)	(−3.16)	(−3.38)	(−1.25)	(−1.45)	(−1.78)
Ln(Assets)		3.498**	4.313**		−19.48***	−14.71***
		(2.11)	(2.46)		(−4.79)	(−3.37)
EDF		18.7***	19.7***		134.9***	127***
		(3.72)	(4.23)		(5.32)	(4.99)
Tangibility		24.69***	27.05***		−37**	−33.23**
		(4.25)	(4.64)		(−2.26)	(−2.04)
Leverage		32.16***	34.02***		30.91**	15.18
		(4.41)	(4.77)		(2.17)	(1.03)
Current Ratio		−3.688***	−3.713***		3.055*	1.015
		(−2.77)	(−2.99)		(1.70)	(0.66)
Ln(1+Int. Cover. Ratio)		−13.62***	−13.53***		−13.13***	−15.03***
		(−9.32)	(−9.47)		(−5.86)	(−8.57)
Years since IPO		−29.36	−10.48		132.4**	138.5**
		(−0.57)	(−0.18)		(2.37)	(2.17)
Ln(Loan Maturity)			.6531			11.44***
			(0.63)			(3.75)
Ln(Lenders)			−.735			−6.604***
			(−0.85)			(−3.08)
Ln(Loan Amount)			−1.098*			1.049
			(−1.75)			(0.35)
Revolver Fraction			1.818*			−52.63***
			(1.93)			(−6.95)
Bank×YearQtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	–	Yes	Yes	–	Yes	Yes
Rating FE	–	Yes	Yes	–	Yes	Yes
Loan Purpose FE	–	–	Yes	–	–	Yes
Adj. R^2	.074	.565	.57	.278	.749	.779
Observations	9,834	4,653	4,643	9,834	4,653	4,643

Table 5. Bank specialization and loan terms, accounting for bank-firm lending relationships

This table reports the estimates of the coefficients from the following regression over our baseline sample, which includes loans for which the loan covenant strictness and all-in drawn spread are available:

$$Loan\ Term_{f,b,t} = \alpha + \theta_{b,t} + FEs + \beta \cdot Specialization_{f,b,t-1} + \beta_R \cdot REL_{f,b,t-1} + \gamma \cdot X_{f,b,t} + \varepsilon_{f,b,t}$$

in which $Loan\ Term_{f,b,t}$ is either the covenant strictness (columns 1 to 3) or the all-in drawn spread (columns 4 to 6) for a loan originated in year-quarter t by bank b to firm f. α is the common intercept, $\theta_{b,t}$ represents bank×year-quarter fixed effects, and *FEs* include, depending on the specification, firm fixed effects, firm rating fixed effects, loan purpose fixed effects. REL represent the relationship lending variable(s), and $X_{f,b,t}$ represents firm and loan controls. All the variables are defined in Table 1. In parentheses, t statistics obtained from two-way clustering at the bank and borrower level. ***, **, * indicate statistical significance at the 1%, 5% and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Panel A: COVENANT STRICTNESS			
Specialization	−24.46***	−24.39***	−24.31***	−24.29***	−24.47***	−24.41***	−24.37***
	(−3.41)	(−3.38)	(−3.37)	(−3.37)	(−3.40)	(−3.39)	(−3.38)
Rel. Length	.107				.104	.123	.126
	(0.73)				(0.70)	(0.79)	(0.81)
Previous Rel.		.259			.088		
		(0.26)			(0.089)		
Rel. Intensity (Amt)			−.306			−.523	
			(−0.30)			(−0.48)	
Rel. Intensity (Num)				−.401			−.620
				(−0.37)			(−0.56)
				Panel B: ALL-IN DRAWN SPREAD			
Specialization	−31.22*	−31.28*	−31.38*	−31.3*	−30.92*	−31*	−30.96*
	(−1.76)	(−1.75)	(−1.75)	(−1.74)	(−1.73)	(−1.74)	(−1.73)
Rel. Length	−.581*				−.496	−.509*	−.523*
	(−1.98)				(−1.63)	(−1.69)	(−1.70)
Previous Rel.		−3.40**			−2.58		
		(−2.20)			(−1.65)		
Rel. Intensity (Amt)			−3.12			−2.23	
			(−1.65)			(−1.19)	
Rel. Intensity (Num)				−2.80			−1.89
				(−1.43)			(−0.95)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank×YearQtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,643	4,643	4,643	4,643	4,643	4,643	4,643

Table 6. Bank specialization and loan terms, accounting for bank industry market share

This table reports the estimates of the coefficients from the following regression over our baseline sample, which includes loans for which the loan covenant strictness and all-in drawn spread are available:

$$\textit{Loan Term}_{f,b,t} = \alpha + \theta_{b,t} + \textit{FEs} + \beta \cdot \textit{Specialization}_{f,b,t-1} + \beta_M \cdot \textit{Mkt Share}_{f,b,t-1} + \gamma \cdot X_{f,b,t} + \varepsilon_{f,b,t}$$

in which $\textit{Loan Term}_{f,b,t}$ is either the covenant strictness (columns 1 to 3) or the all-in drawn spread (columns 4 to 6) for a loan originated in year-quarter t by bank b to firm f. α is the common intercept, $\theta_{b,t}$ represents bank×year-quarter fixed effects, and *FEs* include, depending on the specification, firm fixed effects, firm rating fixed effects, loan purpose fixed effects. $X_{f,b,t}$ represents firm and loan controls. All the variables are defined in Table 1. In parentheses, t statistics obtained from two-way clustering at the bank and borrower level. ***, **, * indicate statistical significance at the 1%, 5% and 10%, respectively.

	Covenant Strictness			All-In Drawn Spread		
	(1)	(2)	(3)	(4)	(5)	(6)
Specialization	−11.39**	−24.34***	−25.1***	−8.503	−30.11	−34.16*
	(−2.20)	(−3.30)	(−3.52)	(−0.78)	(−1.52)	(−1.90)
Market Share	−8.375	8.45	8.337	−47.17	18.04*	26.6***
	(−0.87)	(1.19)	(1.25)	(−1.29)	(1.73)	(2.74)
Bank×YearQtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	—	Yes	Yes	—	Yes	Yes
Rating FE	—	Yes	Yes	—	Yes	Yes
Firm Controls	—	Yes	Yes	—	Yes	Yes
Loan Purpose FE	—	—	Yes	—	—	Yes
Loan Controls	—	—	Yes	—	—	Yes
Adj. R^2	.074	.565	.57	.279	.749	.779
Observations	9,834	4,653	4,643	9,834	4,653	4,643

Table 7. Bank specialization and loan terms, accounting for bank-firm geographical proximity

This table reports the estimates of the coefficients from the following regression over our baseline sample, which includes loans for which the loan covenant strictness and all-in drawn spread are available:

$$\textit{Loan Term}_{f,b,t} = \alpha + \theta_{b,t} + \textit{FEs} + \beta \cdot \textit{Specialization}_{f,b,t-1} + \beta_S \cdot \textit{Same State}_{f,b,t-1} + \gamma \cdot X_{f,b,t} + \varepsilon_{f,b,t}$$

in which $\textit{Loan Term}_{f,b,t}$ is either the covenant strictness (columns 1 to 3) or the all-in drawn spread (columns 4 to 6) for a loan originated in year-quarter t by bank b to firm f. α is the common intercept, $\theta_{b,t}$ represents bank×year-quarter fixed effects, and *FEs* include, depending on the specification, firm fixed effects, firm rating fixed effects, loan purpose fixed effects. $X_{f,b,t}$ represents firm and loan controls. All the variables are defined in Table 1. In parentheses, t statistics obtained from two-way clustering at the bank and borrower level. ***, **, * indicate statistical significance at the 1%, 5% and 10%, respectively.

	Covenant Strictness			All-In Drawn Spread		
	(1)	(2)	(3)	(4)	(5)	(6)
Specialization	−13.72**	−23.35**	−24.16**	−8.307	−37.37*	−38.8*
	(−2.32)	(−2.43)	(−2.76)	(−0.67)	(−1.73)	(−1.85)
Same State	−.0431	−.6604	−.8592	−8.508	−7.705	−7.132
	(−0.021)	(−0.20)	(−0.25)	(−1.13)	(−1.08)	(−1.07)
Bank×YearQtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	–	Yes	Yes	–	Yes	Yes
Rating FE	–	Yes	Yes	–	Yes	Yes
Firm Controls	–	Yes	Yes	–	Yes	Yes
Loan Purpose FE	–	–	Yes	–	–	Yes
Loan Controls	–	–	Yes	–	–	Yes
Adj. R^2	.072	.576	.58	.268	.755	.781
Observations	9,072	4,267	4,259	9,072	4,267	4,259

Table 8. Bank specialization and loan terms after defaults on banks' portfolio

This table reports the estimates of the coefficients from the following regression over our baseline sample, which includes loans for which the loan covenant strictness and all-in drawn spread are available:

$$Loan\ Term_{f,b,t} = \alpha + \theta_{b,t} + FEs + \beta Specialization_{f,b,t-1} + \beta_D DEF_{b,t-1} + \delta Specialization_{f,b,t-1} * DEF_{b,t-1} + \gamma \cdot X_{f,b,t} + \varepsilon_{f,b,t}$$

in which $Loan\ Term_{f,b,t}$ is either the covenant strictness (columns 1 to 3) or the all-in drawn spread (columns 4 to 6) for a loan originated in year-quarter t by bank b to firm f. α is the common intercept, $\theta_{b,t}$ represents bank×year-quarter fixed effects, and *FEs* include, depending on the specification, firm fixed effects, firm rating fixed effects, loan purpose fixed effects. $X_{f,b,t}$ represents firm and loan controls. All the variables are defined in Table 1. In parentheses, t statistics obtained from two-way clustering at the bank and borrower level. ***, **, * indicate statistical significance at the 1%, 5% and 10%, respectively.

	Covenant Strictness					
	(1)	(2)	(3)	(4)	(5)	(6)
Specialization	−24.36***	−25.3***	−25.29***	−22.73***	−23.6***	−23.59***
	(−3.38)	(−3.25)	(−3.24)	(−2.98)	(−2.79)	(−2.79)
Specialization * Defaults (Same)	30.28**		30.35**	30.71**		30.76**
	(2.28)		(2.28)	(2.34)		(2.34)
Specialization * Defaults (Other)		2.073	2.075		1.837	1.839
		(0.40)	(0.40)		(0.34)	(0.34)
Defaults (Same)	.8011		.8048	.7885		.7921
	(1.02)		(1.02)	(1.01)		(1.01)
Defaults (Other)		−.824			−.8116	
		(−1.05)			(−1.04)	
Industry Portfolio Share				−9.782	−9.547	−9.562
				(−0.94)	(−0.89)	(−0.89)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank×YearQtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	.57	.57	.57	.57	.57	.57
Observations	4,643	4,643	4,643	4,643	4,643	4,643

Table 9. Robustness: sample restricted to loans with a single lead arranger

This table reports the estimates of the coefficients from the following regression over the baseline sample, further restricted to include only loans with a single-lead arranger:

$$\textit{Loan Term}_{f,b,t} = \alpha + \theta_{b,t} + \textit{FEs} + \beta \cdot \textit{Specialization}_{f,b,t-1} + \gamma \cdot X_{f,b,t} + \varepsilon_{f,b,t}$$

in which $\textit{Loan Term}_{f,b,t}$ is either the covenant strictness (columns 1 to 3) or the all-in drawn spread (columns 4 to 6) for a loan originated in year-quarter t by bank b to firm f. α is the common intercept, $\theta_{b,t}$ represents bank×year-quarter fixed effects, and *FEs* include, depending on the specification, firm fixed effects, firm rating fixed effects, loan purpose fixed effects. $X_{f,b,t}$ represents firm and loan controls. All the variables are defined in Table 1. In parentheses, t statistics obtained from two-way clustering at the bank and borrower level. ***, **, * indicate statistical significance at the 1%, 5% and 10%, respectively.

	Covenant Strictness			All-In Drawn Spread		
	(1)	(2)	(3)	(4)	(5)	(6)
Specialization	-11.67^{**}	-17.32^{**}	-18.59^{**}	-15.53	-34.28	-37.66^{*}
	(-2.23)	(-2.05)	(-2.30)	(-1.28)	(-1.46)	(-1.76)
Bank×YearQtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	—	Yes	Yes	—	Yes	Yes
Rating FE	—	Yes	Yes	—	Yes	Yes
Firm Controls	—	Yes	Yes	—	Yes	Yes
Loan Purpose FE	—	—	Yes	—	—	Yes
Loan Controls	—	—	Yes	—	—	Yes
Adj. R^2	.071	.564	.569	.28	.751	.778
Observations	9,370	4,359	4,348	9,370	4,359	4,348

Table 10. Robustness: bank specialization measure calculated using data from 1996

This table reports the estimates of the coefficients from the following regression over the baseline sample:

$$\textit{Loan Term}_{f,b,t} = \alpha + \theta_{b,t} + \textit{FEs} + \beta \cdot \textit{Specialization (96)}_{f,b,t-1} + \gamma \cdot X_{f,b,t} + \varepsilon_{f,b,t}$$

in which *Loan Term*$_{f,b,t}$ is either the covenant strictness (columns 1 to 3) or the all-in drawn spread (columns 4 to 6) for a loan originated in year-quarter t by bank b to firm f. α is the common intercept, $\theta_{b,t}$ represents bank×year-quarter fixed effects, and *FEs* include, depending on the specification, firm fixed effects, firm rating fixed effects, loan purpose fixed effects. $X_{f,b,t}$ represents firm and loan controls. All the variables are defined in Table 1. In parentheses, t statistics obtained from two-way clustering at the bank and borrower level. ***, **, * indicate statistical significance at the 1%, 5% and 10%, respectively.

	Covenant Strictness			All-In Drawn Spread		
	(1)	(2)	(3)	(4)	(5)	(6)
Specialization (96)	−11.9**	−23.56***	−24.33***	−8.043	−28.45	−31.76*
	(−2.52)	(−3.16)	(−3.38)	(−0.59)	(−1.45)	(−1.78)
Bank×YearQtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	—	Yes	Yes	—	Yes	Yes
Rating FE	—	Yes	Yes	—	Yes	Yes
Firm Controls	—	Yes	Yes	—	Yes	Yes
Loan Purpose FE	—	—	Yes	—	—	Yes
Loan Controls	—	—	Yes	—	—	Yes
Adj. R^2	.081	.566	.571	.281	.75	.779
Observations	8,990	4,648	4,638	8,990	4,648	4,638

Table 11. Robustness: sample restricted to loans originated before 2008

This table reports the estimates of the coefficients from the following regression over the baseline sample, further restricted to include only loans originated before (excluding) 2008:

$$Loan\ Term_{f,b,t} = \alpha + \theta_{b,t} + FEs + \beta \cdot Specialization_{f,b,t-1} + \gamma \cdot X_{f,b,t} + \varepsilon_{f,b,t}$$

in which $Loan\ Term_{f,b,t}$ is either the covenant strictness (columns 1 to 3) or the all-in drawn spread (columns 4 to 6) for a loan originated in year-quarter t by bank b to firm f. α is the common intercept, $\theta_{b,t}$ represents bank×year-quarter fixed effects, and *FEs* include, depending on the specification, firm fixed effects, firm rating fixed effects, loan purpose fixed effects. $X_{f,b,t}$ represents firm and loan controls. All the variables are defined in Table 1. In parentheses, t statistics obtained from two-way clustering at the bank and borrower level. ***, **, * indicate statistical significance at the 1%, 5% and 10%, respectively.

	Covenant Strictness			All-In Drawn Spread		
	(1)	(2)	(3)	(4)	(5)	(6)
Specialization	-14.6^{**}	-30.15^{***}	-32.83^{***}	-17.29	-16.57	-17.77
	(-2.54)	(-2.86)	(-2.87)	(-1.33)	(-0.48)	(-0.59)
Bank×YearQtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	—	Yes	Yes	—	Yes	Yes
Rating FE	—	Yes	Yes	—	Yes	Yes
Firm Controls	—	Yes	Yes	—	Yes	Yes
Loan Purpose FE	—	—	Yes	—	—	Yes
Loan Controls	—	—	Yes	—	—	Yes
Adj. R^2	.051	.536	.537	.234	.739	.773
Observations	6,832	2,089	2,085	6,832	2,089	2,085

Table 12. Robustness: bank specialization measure computed over different time windows

This table reports the estimates of the coefficients on the *Specialization* variable—averaged over different time windows—from the following regression over our baseline sample:

$$\textit{Loan Term}_{f,b,t} = \alpha + \theta_{b,t} + \textit{FEs} + \beta \cdot \textit{Specialization}\ (n\mathrm{Y})_{f,b,t-1} + \gamma \cdot X_{f,b,t} + \varepsilon_{f,b,t}$$

in which $\textit{Loan Term}_{f,b,t}$ is either the covenant strictness (columns 1 to 3) or the all-in drawn spread (columns 4 to 6) for a loan originated in year-quarter t by bank b to firm f. α is the common intercept, $\theta_{b,t}$ represents bank×year-quarter fixed effects, and *FEs* include, depending on the specification, firm fixed effects, firm rating fixed effects, loan purpose fixed effects. $X_{f,b,t}$ represents firm and loan controls. All the variables are defined in Table 1. In parentheses, t statistics obtained from two-way clustering at the bank and borrower level. ***, **, * indicate statistical significance at the 1%, 5% and 10%, respectively.

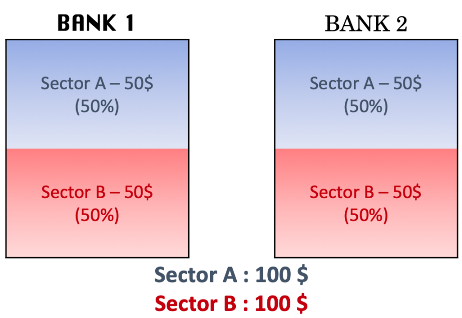
	Covenant Strictness					All-In Drawn Spread				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Specialization (1Y)	−8.303					−33.57**				
	(−1.14)					(−2.64)				
Specialization (2Y)		−15.93*					−37.91**			
		(−1.92)					(−2.39)			
Specialization (3Y)			−24.35***					−31.77*		
			(−3.38)					(−1.78)		
Specialization (4Y)				−23.04***					−29.41	
				(−2.76)					(−1.42)	
Specialization (5Y)					−20.32**					−16.33
					(−2.25)					(−0.72)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank×YearQtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	.569	.568	.57	.572	.57	.779	.779	.779	.777	.776
Observations	4,767	4,701	4,643	4,576	4,455	4,767	4,701	4,643	4,576	4,455

Appendix B. Figures

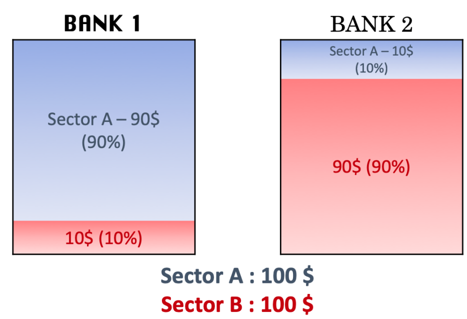
Figure 1. Simple examples to understand bank specialization

This figure reports simplified examples from two-bank, two-sector lending markets. From the top left, we can see: (a) an example of no specialized banks; (b) an example of specialized banks – Bank 1 in sector A and Bank 2 in sector B; (c) a case in which no bank is specialized because both banks allocate the same portfolio shares to both sectors; (d) a case in which both banks are specialized – Bank 1 in lending to sector A and Bank 2 in lending to sector B.

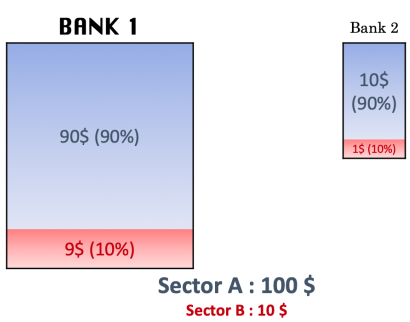
(a) Neither bank is specialized



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



(c) Neither bank is specialized



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

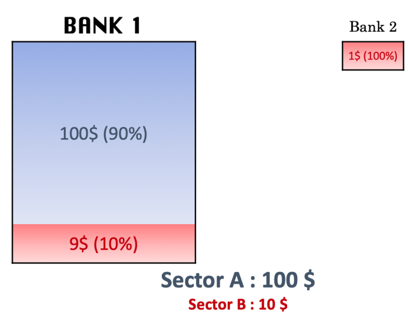


Figure 2. Comparison between portfolio concentration of the average bank and the "market"

This figure plots on the y-axis the *HHI* measure of loan portfolio concentration, and on the x-axis the year at which it is recorded. *HHI* is computed for the Market (blue) and Average Bank (green) portfolios per each year-quarter. A higher value of *HHI* implies that lending to sectors is more concentrated in the market/average bank's portfolio. The fact that the average bank is systematically characterized by a higher *HHI* compared to the market shows graphically that the average lender in the syndicated loan market remained overall more concentrated than the whole syndicated market over 1996-2016.

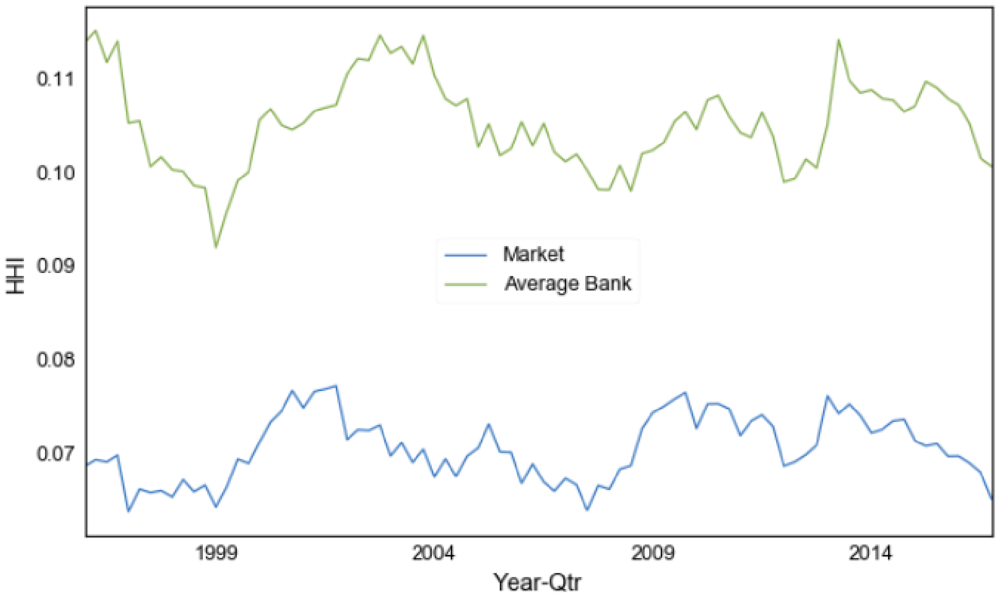


Figure 3. Specialization is common across industries and time

This figure presents evidence of specialization in lending towards specific industries in four different moments from our sample: 2000q2, 2005q2, 2010q2, 2015q2. Each subfigure reports the box-plot graph, for each of the 25 TFIC industries, of the distribution of banks' demeaned loan portfolio shares in a given industry. Each dot represents an outlier, and therefore, a banks specialized in that industry.

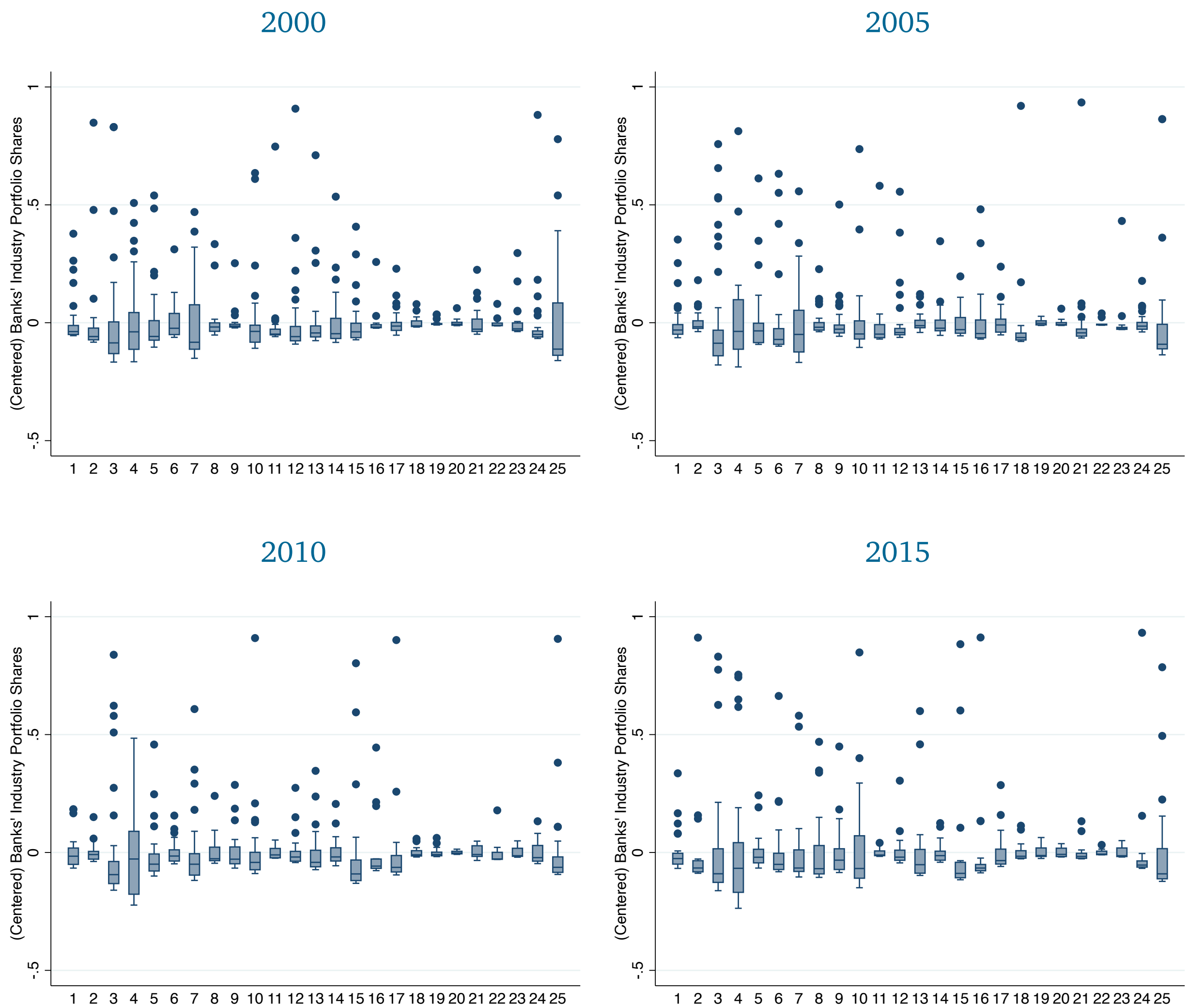


Figure 4. Specialization is persistent over time

This figure plots the *n*-year autocorrelation of the specialization dummy, averaged at the bank-year-sector level, where *n* takes value from 1 to 10.