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Essays On Banking And Credit Markets

Abstract

This dissertation focuses on two themes in the field of empirical banking. First, the importance of credit relationships for corporations experiencing financial distress; second, the relevance of credit market structure for the price and non-price terms associated with the provision of credit.

The first chapter investigates whether relationship lending helps firms experiencing idiosyncratic financial distress. By constructing a novel dataset on syndicated lending that tracks the availability and pricing of credit for US corporate borrowers over three decades, I conclude that relationship lending benefits borrowers in distress. Specifically, I find that relationship lenders provide a higher credit amount, charge lower interest rates, and require similar collateral and fees, relative to non-relationship lenders. Firms benefit from relationship lending irrespective of their access to outside financing options. Overall, my findings provide support to theories of implicit commitment and reputational capital in lending relationships.

The second chapter focuses on the importance of bank specialization in monitoring specific projects for the design of loan contracts. Using detailed information on credit relationships in the US syndicated loan market, I first document that banks specialize in lending to specific industries. Specialization is common across industries and persistent over time. Then, I provide evidence that specialized banks provide credit with looser restrictions (covenants) and at lower cost (interest rates) when arranging loans in their sector of specialization. This is consistent with an explanation of bank specialization based on monitoring advantages. Overall, the laxer contract terms offered by specialized banks could provide an explanation for recent evidence that firms cannot easily substitute credit granted by specialized banks.

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ESSAYS ON BANKING AND CREDIT MARKETS

Marco Giometti

A DISSERTATION

in

Finance

For the Graduate Group in Managerial Science and Applied Economics

Presented to the Faculties of the University of Pennsylvania

in

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Supervisor of Dissertation

David Musto, Ronald O. Perelman Professor in Finance

Graduate Group Chairperson

Nancy Zhang, Ge Li and Ning Zhao Professor, Professor of Statistics

Dissertation Committee

Richard J. Herring, Jacob Safra Professor of International Banking, Professor of Finance
Lorena Keller, Assistant Professor of Finance

ABSTRACT

ESSAYS ON BANKING AND CREDIT MARKETS

Marco Giometti

David Musto

This dissertation focuses on two themes in the field of empirical banking. First, the importance of credit relationships for corporations experiencing financial distress; second, the relevance of credit market structure for the price and non-price terms associated with the provision of credit.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF ILLUSTRATIONS

CHAPTER 1

RELATIONSHIP LENDING WHEN BORROWERS ARE IN DISTRESS

Is it valuable for firms to establish and maintain a bank credit relationship? Do stronger bank relationships help corporate borrowers when they experience financial distress? The outstanding literature offers contrasting answers to these questions. We know that banks often act as relationship lenders, acquiring private information on their borrowers over time through repeated interactions (Boot, 2000). Yet, from a theoretical perspective there are both benefits and costs associated with strong lending relationships. From an empirical perspective, the benefits generally appear to outweigh the costs, especially during normal economic circumstances and times of aggregate distress.[1]

We know less about the implications of establishing a strong lending relationship in circumstances of idiosyncratic borrower distress outside of crisis times.[2] Filling this gap is relevant for several reasons. First, financial distress is costly. Estimates put the costs of financial distress in the range of 10 to 25% of pre-distressed firm value (Andrade & Kaplan, 1998; Davydenko, Strebulaev, & Zhao, 2012). Second, lenders are likely to play an important role in out-of-court renegotiations to resolve situations of distress (Campello, Ladika, & Matta, 2018; Gilson, John, & Lang, 1990). Third, from a firm risk management perspective, it is important to understand whether an established credit relationship could mitigate the costs associated with distress.

1. For evidence that relationship lending benefits firms in normal times, see: Berger and Udell (1995); Bharath, Dahiya, Saunders, and Srinivasan (2007, 2011); Dahiya, Hallak, and Matthys (2021); Degryse and Ongena (2005); Drucker and Puri (2005); Petersen and Rajan (1994); Schenone (2010). For evidence that relationship lending provides insurance during financial crises and times of aggregate distress, see: Beck, Degryse, De Haas, and Van Horen (2018); Berlin and Mester (1999); Bolton, Freixas, Gambacorta, and Mistrulli (2016); DeYoung, Gron, Torna, and Winton (2015); Jiménez, Ongena, Peydró, and Saurina (2012); Karolyi (2018); Sette and Gobbi (2015).

2. The existing empirical evidence is scant, and the results are mixed. Elsas and Krahnen (1998), Hoshi, Kashyap, and Scharfstein (1990), and Schäfer (2019) provide evidence that stronger credit relationships benefit firms in distress through liquidity insurance. Peek and Rosengren (2005) find that lenders with strong corporate affiliations to firms have a higher propensity to "evergreen" loans when firms are in trouble, to avoid the realization of losses on their balance sheets. Li, Lu, and Srinivasan (2019) instead find no effect of relationship lending on credit terms when borrowers are in distress.

Theories of relationship lending offer competing predictions on this issue. First, relationship lenders could provide insurance to borrowers in distress, either to extract higher rents in normal times (Berlin & Mester, 1999; Bolton et al., 2016; Petersen & Rajan, 1995), honor implicit commitment and preserve reputational capital (Boot, Greenbaum, & Thakor, 1993; Dinç, 2000), or avoid the realization of possible losses on their balance sheet (Dewatripont & Maskin, 1995; Hu & Varas, 2021). Second, relationship banks could hold up their borrowers, exploiting the presence of informational monopolies (Rajan, 1992; Sharpe, 1990). Third, there might be no difference between borrowing from relationship or non-relationship lenders for firms in distress. If lenders engage in relationship lending mainly to win future lending and non-lending business (Bharath et al., 2007; Drucker & Puri, 2005), they might not give any preferential treatment to borrowers in distress because at that point the continuation value of the relationship could be very low.

The objective of this paper is therefore to empirically investigate whether relationship lending helps borrowers when they experience idiosyncratic financial distress, in the context of the US syndicated loan market. To achieve this goal, I explicitly distinguish loan renegotiations from new originations, and account for the state-contingent provisions on loan pricing present in a large fraction of credit agreements. This allows me to construct a novel dataset that tracks the availability and pricing of credit for US corporate borrowers over three decades, similar to a credit register. I exploit this dataset to compare the loan terms granted to borrowers in distress by relationship and non-relationship lenders. By employing a within-firm approach to alleviate possible selection issues, I find that relationship lenders provide a higher credit amount, charge lower interest rates, and require similar collateral and fees. I also show that firms benefit from relationship lenders irrespective of their access to alternative financing options. Overall, my findings provide support to theories of implicit commitment and reputational capital in lending relationships.

In order to perform my analysis, I obtain data on a large sample of syndicated loans over the period 1987-2016 from Refinitiv/Thomson Reuters Dealscan, one of the most common data source for research in bank lending and financial contracting. Unlike most of the existing literature, I also obtain detailed information on loan modifications and on performance pricing grids available in the corresponding tables in Dealscan.[3] Using the linking tables provided by Chava and Roberts (2008) and Schwert (2018), I merge each loan observation from Dealscan with borrower and lender characteristics obtained from CRSP/Compustat and Compustat Bank, as well as information on bond issuances from Mergent FISD.

I measure relationship lending by closely following its theoretical definition. In theory, a bank acts as a relationship lender by acquiring non-contractible, private information about its borrowers through repeated interactions. That is why I use the total number of loan events in Dealscan—both new originations and renegotiations—between a borrower and a specific lender over a rolling five-year window to characterize the strength of a credit relationship. This is standardized by the total number of loan events between the borrower and any lender in the same five-year window.[4,5]

I measure financial distress by relying on the expected default probability implied by the Merton model of credit risk (Merton, 1974). This measure has several advantages over other measures used in the literature, such as the Altman Z-Score (Altman, 1968). It is a market-based, forward-looking measure, it can be easily computed from stock price and balance sheet data on a monthly frequency, and it is based on the same model as Moody's KMV, a leading indicator of credit risk widely employed in the financial industry. In practice, I follow the "naive" implementation proposed by Bharath and Shumway (2008). I compute the EDF for the universe of CRSP/Compustat firms over the period 1987-2016. Then, I define a given firm to be in distress in a given quarter if over the previous four quarters the firm's EDF was in the top quartile of the overall distribution of EDFs for six or more months.

3. Notable exceptions include Chodorow-Reich (2014), who also uses information on loan modifications, and Adam and Streitz (2016) and Asquith, Beatty, and Weber (2005), who specifically analyze the role of performance pricing in syndicated loans.
4. This measure is commonly used in the literature that studies relationship lending in the context of the syndicated loan market. For example, see: Bharath et al. (2007, 2011); Prilmeier (2017); Schenone (2010).
5. In robustness tests I also use a similar measure weighted by loan amounts, and a dummy variable which capture whether the borrower has interacted with a given lender at least once over the same time window.

Equipped with these measures of relationship lending and financial distress, I aim to estimate the causal effect of relationship lending on credit terms when borrowers experience financial distress. To credibly achieve this goal, I need to overcome two main empirical challenges. First, credit terms can change even absent a new loan origination. Specifically, loan agreements can be renegotiated and often contain prespecified state-contingent provisions. Both features could be particularly relevant in distress. On the one hand, it is reasonable that lenders would renegotiate an existing loan rather than originate a new one. On the other hand, terms could automatically change as a borrower enters distress.[6] This issue could be compounded by a different propensity to use state-contingent loan pricing provisions by relationship and non-relationship lenders (Adam & Streitz, 2016).

Second, the matching between banks and firms is non-random, and selection issues could arise. For example, empirical evidence points to firm and bank size as an important determinant of matching (Berger, Miller, Petersen, Rajan, & Stein, 2005; Chen & Song, 2013; Cole, Goldberg, & White, 2004; Hubbard, Kuttner, & Palia, 2002; Stein, 2002). Schwert (2018) documents that more opaque firms borrow from more capitalized banks. Thus, borrowers that establish and maintain strong credit relationships could be significantly different than borrowers who do not.

I address these challenges in two ways. First, I construct a novel dataset on syndicated lending that spans three decades and resembles a credit register for US corporate borrowers, with information on the availability and pricing of credit at the loan-quarter level for each borrower. In particular, I proceed as follows. I distinguish new loan originations from renegotiations thanks to an algorithm that extracts information from comments to credit agreements. I then assume that a loan agreement is outstanding in either until its stated maturity date or until it is renegotiated. By looking at loan modifications, I can also capture further changes to credit terms over the lifetime of a loan. Finally, I track the pricing of loans over time by explicitly considering the presence of performance pricing grids, and mapping

6. Renegotiations and the use of state-contingent provisions are generally considered substitutes; Nikolaev (2018) provides empirical evidence consistent with this notion.

the relevant borrower's performance variable to the level of interest rate spreads and fees specified by the grid.

Second, in my empirical strategy I employ a within-firm approach, which should alleviate possible selection issues. To account for the potentially non-random matching of borrowers and lenders, I control for bank unobserved heterogeneity and time-varying drivers of matching, such as bank capital. Intuitively, my empirical approach consists of comparing the terms of loans to the same borrower granted by two different lenders, characterized by different relationship strengths, in and outside of distress.

Overall, I find strong evidence that relationship lending helps borrowers in distress. In particular, borrowers obtain from their relationship lenders a higher amount of credit and lower interest rate relative to non-relationship lenders. These benefits are economically relevant. A one standard deviation increase in the strength of the lending relationship implies a higher credit availability in distress by 5.3%, which amounts to approximately $8M for the median loan, and a lower cost of credit by 3.9-4.5 basis points, which translates into up to $300,000 of savings over the lifetime of the median loan. Importantly, these effects are not offset by higher commitment fees, collateral requirements, or upfront fees. These results are inconsistent with theories of lender hold-up (Rajan, 1992; Sharpe, 1990; von Thadden, 1995) and provide support to theories of relationship lending predicting insurance provision to borrowers in distress.

In principle, lenders could provide favorable terms to their relationship borrowers in distress for three different reasons. First, they could engage in a value-enhancing intertemporal smoothing of interest rates: lenders provide favorable terms in distress so that they can extract higher rents in normal times (Berlin & Mester, 1999; Bolton et al., 2016; Petersen & Rajan, 1995). Second, lenders could provide insurance in distress to honor implicit commitments, thereby preserving or developing a reputation for providing financial flexibility to borrowers in distress (Boot et al., 1993; Chemmanur & Fulghieri, 1994; Dinç, 2000). Third, it could be optimal for lenders to refinance borrowers in distress (Dewatripont & Maskin, 1995; Hu & Varas, 2021; Puri, 1999). Their borrowers, internalizing this, could obtain favorable terms by threatening to declare default and holding up their lenders (Davydenko & Strebulaev, 2007).

Each set of theories has different cross-sectional predictions on which borrowers are more likely to benefit from relationship lending during distress. Theories of *intertemporal smoothing* predict that credit terms should be relatively more favorable for borrowers with lower outside options, as they are more likely to accept a higher cost of credit in good times to obtain insurance in bad times. Theories of *borrower hold-up* predict the opposite, as banks should be more willing to keep providing credit to borrowers with access to a broader menu of financing options, which would therefore have a higher incentive to strategically threaten default and obtain better terms. Finally, according to theories of *implicit commitment* and *reputational capital* there should not be any significant difference across borrowers with different outside options.

Motivated by these different theories, I investigate the role of borrowers' outside financing options to shed further light on the actual economic mechanisms at work. I employ the access to public bond markets to capture the degree of borrowers' outside financing options. Firms that issue bonds are likely to have a broader menu of financing options and are characterized by more public information available to market participants—through the market price of their bonds and the analysis of their underwriters (Hale & Santos, 2009; Santos & Winton, 2008).

I repeat my analysis over subsamples of borrowers based on their access to public debt markets. In practice, I perform the subsample analyses using different proxies for bond market access. First, I split loans based on whether the borrower issued at least one public bond at any time before the current loan, or not. Second, I split loans based on whether the borrower issued a public bond in the three years before the current loan, or not. The latter is likely to better capture the current availability of public information about the borrowers compared to the former (Santos & Winton, 2019). In both analyses, I find that borrowers in distress benefit from relationship lending irrespectively of their outside options, though in a qualitatively different way. Borrowers with outside options obtain higher credit amounts, whereas borrowers with no outside options obtain favorable price terms. Overall, these findings are mainly consistent with theories of implicit commitment and reputational capital in lending relationships.

The rest of the paper proceeds as follows. In Section 1.1 I review the related literature and highlight the contribution of this paper. In Section 1.2, I discuss theories of relationship lending and their implications for credit terms when borrowers experience distress, which result in several testable hypotheses. In Section 1.3, I describe the data sources, the various steps to track renegotiations and loan pricing terms over time, and the measurement of the economic variables. In Section 2.3, I present the results of the empirical analysis and offer an economic interpretation in light of the existing theories. Section 1.5 offers concluding remarks.

1.1. Related Literature and Contribution

This paper contributes to several strands of literature. First, it advances our understanding on the benefits and costs of lending relationships. Several studies provide evidence consistent with a beneficial role of relationship lending both in normal times (Berger & Udell, 1995; Bharath et al., 2007, 2011; Dahiya et al., 2021; Degryse & Ongena, 2005; Drucker & Puri, 2005; Petersen & Rajan, 1994; Schenone, 2010) and in times of aggregate distress (Beck et al., 2018; Berlin & Mester, 1999; Bolton et al., 2016; DeYoung et al., 2015; Jiménez et al., 2012; Karolyi, 2018; Sette & Gobbi, 2015). However, there is also some evidence pointing to a less benign side of relationship lending both in normal times (Calomiris & Pornrojnangkool, 2009; Degryse & Cayseele, 2000) and in times of aggregate distress (Berger et al., 2021; Santos & Winton, 2008). A smaller body of works focuses on situations in which borrowers experience distress, mostly in bank-dominated economies such as Germany and Japan (Elsas & Krahnen, 1998; Hoshi et al., 1990; Peek & Rosengren, 2005; Schäfer, 2019). Consistent with the results of this paper, they provide evidence that stronger bank relationships benefit firms when they undergo financial distress.

My results are in contrast with the evidence presented by Li et al. (2019), who also analyze the implications of relationship lending for borrowers in distress in the context of the US syndicated loan market. In particular, I find a beneficial effect of relationship lending on credit terms, whereas they conclude that there are no benefits in this regards. This is due to several important differences in the empirical approach between this paper and their work. First, I include all loan renegotiations in the computation of the measures of relationship lending. This improves on the characterization of relationship lending, since a renegotiation is a direct way to observe the presence of an active lending relationship. Second, I account for state-contingent loan pricing. In presence of differential use of these provisions by relationship and non-relationship lenders, this allows for a more precise counterfactual loan spread as borrowers enter distress. Third, I focus on a broader set of loan terms compared to Li et al. (2019), who do not analyze loan amounts.[7] Fourth, differently from Li et al. (2019), I explicitly account for bank unobserved variation and control for important time-varying drivers of bank matching, such as bank size and bank capital. Fifth, I exploit cross-sectional heterogeneity in borrowers' outside options to discriminate among different economic theories.

This paper also contributes to the literature on loan renegotiations (Berlin & Mester, 1992; Nikolaev, 2018; Roberts, 2015; Roberts & Sufi, 2009b; Xiang, Wang, & Basu, 2021). While focusing on the outcomes of both new loan originations and renegotiations, this paper develops an algorithm to distinguish originations from renegotiations that allows for a large-sample analysis of renegotiations, similar to Nikolaev (2018). While Nikolaev (2018) obtains information by scraping the credit agreements directly from the SEC filings, I rely on comments in the Dealscan database to classify renegotiations. Moreover, I use this information to construct a pseudo credit register that covers three decades. By looking also at the outcomes renegotiations when borrowers are in distress over a long time sample in the US, this paper complements the study by Papoutsi (2021), who analyzes how relationship lending affects

7. They also look at the degree of covenant strictness.

the likelihood and the outcomes of loan renegotiations in Greece against the backdrop of the Greek sovereign debt crisis.

Finally, this paper is broadly related to the literature on financial contracting (see, e.g., Roberts & Sufi, 2009a) and in particular to a smaller, but growing set of studies that focus on performance pricing (Adam & Streitz, 2016; Asquith et al., 2005; Bensoussan, Chevalier-Roignant, & Rivera, 2021; Bhanot & Mello, 2006; Chaigneau, Edmans, & Gottlieb, 2021; Koziol & Lawrenz, 2010; Manso, Strulovici, & Tchistyi, 2010). These studies analyze the rationale and the optimality of state-contingent loan pricing provisions, whereas this paper takes these provisions as given and aims to obtain the actual loan pricing terms implied by these provisions quarter by quarter. To the best of my knowledge, I am the first one to explicitly consider performance pricing provisions in this way.

1.2. Conceptual Framework and Hypotheses

There is a large empirical and theoretical literature studying relationship lending and its implications for borrowers, in and outside of financial distress. Theoretical work offers sharply different predictions and mechanisms regarding the impact of relationship lending when borrowers experience distress. Below I review these studies and derive testable hypotheses that will be the focus of the empirical analysis.

Theories of *intertemporal smoothing* (Berlin & Mester, 1999; Bolton et al., 2016; Petersen & Rajan, 1995), *implicit commitment and reputational incentives* (Boot et al., 1993; Dinç, 2000), and *borrower hold-up/zombie lending* (Davydenko & Strebulaev, 2007; Hu & Varas, 2021) predict that borrowers receive favorable terms from relationship lenders compared to non-relationship ones.

Studies emphasizing the *continuation value* and *economies of scope* embedded in credit relationships from the lender's perspective (Bharath et al., 2007; Drucker & Puri, 2005; Yasuda, 2005) posit that relationship lenders offer no different terms than other lenders when borrowers are in distress.

Finally, theories of *lender hold-up* (Rajan, 1992; Sharpe, 1990; von Thadden, 1995) predict that borrowers in distress will obtain worse credit terms from relationship lenders relative to other lenders. Below I review these theories and the corresponding testable hypotheses in more detail.

Hypothesis 1: Better Credit Terms in Distress

Intertemporal Smoothing

Allen and Gale (1997), Berlin and Mester (1999), Bolton et al. (2016), and Petersen and Rajan (1995) present models in which banks can accommodate intertemporal smoothing of interest rates on loans through long-term lending relationships.

In Berlin and Mester (1999), banks can insure borrowers against rising interest rates in times of distress thanks to their access to rate-insensitive sources of funding, namely core deposits. In the theories of Allen and Gale (1997) and Petersen and Rajan (1995) relationship lenders can provide intertemporal risk-sharing against firms experiencing shocks to their credit quality, i.e. distress, if they can expect to recoup possible short-term losses with larger long-term benefits. Similarly, Bolton et al. (2016) show, both theoretically and empirically, that lenders provide relatively favorable interest rates to relationship borrowers during times of aggregate distress because they can charge higher rates in normal times.

A crucial role in this class of models is the presence of some degree of ex-post lender's market power over the borrower. In fact, lenders that face high credit market competition cannot provide insurance in bad times because they do not expect to extract rents in good times. Therefore, the *intertemporal smoothing* hypothesis has the following testable predictions along three dimensions – distress times, normal times, and in the cross-section:

H1.A. In *distress*, relationship borrowers obtain *better* terms than non-relationship.

H1.B. In *normal times*, relationship borrowers obtain *worse* terms than non-relationship.

H1.C. The effects are *stronger* for borrowers *with no, or little, outside financing* *options.*

Implicit Commitment & Reputational Capital

Through repeated interactions with a borrower, relationship lenders can generate information that is proprietary (Bhattacharya & Chiesa, 1995) and reusable (Chan, Greenbaum, & Thakor, 1986). In the presence of economies of scale in information production, the acquisition of information can also generate economies of scope because a relationship lender can offer loans and other services at a lower cost (Petersen & Rajan, 1994). Boot (2000) concludes that relationship lending allows for the acquisition and the use of subtle, non-contractable information that facilitates implicit, long-term contracting. This implies that relationship lending should provide benefits to borrowers in normal times, in the form of favorable credit terms.

Lenders could keep providing preferential treatment to relationship borrowers even in distress, to honor implicit commitment and to preserve their reputation as relationship lenders, despite incurring in potential losses. Boot et al. (1993) explicitly model the trade-off between financial and reputational capital when lenders need to decide whether to keep financing or not borrowers that experience a material adverse change to their financial conditions. They might want to continue supplying credit even in the presence of losses to financial capital in order to develop a reputation for providing support to borrowers in distress. In turn, a good reputation might attract future lending business from other borrowers. Dinç (2000) also presents a model in which relationship lenders should finance borrowers in distress because of reputational concerns. The *implicit contracting* hypothesis has thus the following testable implications:

H1.A. In *distress*, relationship borrowers obtain *better* terms than non-relationship.

H1.D. In *normal times*, relationship borrowers obtain *better* terms than non-relationship.

H1.E. In *distress*, relationship borrowers obtain *similar* terms than what they would obtain in normal times.

Borrower Hold-Up

Another reason why lenders could grant favorable credit terms in distress is to avoid the costs associated with their borrowers' default or bankruptcy events (Dahiya, Saunders, & Srinivasan, 2003). Lenders, exploiting their role as information producer, might also have the incentive to certify a borrower in distress to increase the chances of future market financing, which would allow the borrower to then repay its loans (Puri, 1999). Dewatripont and Maskin (1995) and Hu and Varas (2021) also present model in which it is optimal for the lender to refinance a borrower experiencing distress. Borrowers internalize this, and can therefore threaten to strategically declare default or file for bankruptcy (Davydenko & Strebulaev, 2007), thereby holding up their relationship lenders and extracting better credit terms while experiencing distress.

According to this view, relationship lenders would provide credit terms that not only are relatively more favorable than non-relationship in distress, but that are more favorable even compared to the terms that would be offered in normal times. The studies by Dahiya et al. (2003) and Drucker and Puri (2005) also suggest that this effect should be more pronounced for larger and less opaque borrowers, because the costs associated to these borrowers' default would be higher for the lenders. The *borrower hold-up* hypothesis has thus the following testable implications:

H1.A. In *distress*, relationship borrowers obtain *better* terms than non-relationship.

H1.D. In *normal times*, relationship borrowers obtain *better* terms than non-relationship.

H1.F. In *distress*, relationship borrowers obtain *even better* terms than what they would obtain in normal times.

H1.G. The effects are *stronger* for borrowers *with (better) outside financing options.*

Hypothesis 2: Same Credit Terms in Distress

Continuation Value

An alternative possibility is that lenders do not offer any preferential treatment to relationship borrowers in distress. The reason is that the benefit of such course of action might be limited, at best. Bharath et al. (2007), Drucker and Puri (2005), and Yasuda (2005) offer empirical evidence that is consistent with the notion, discussed earlier in the context of implicit contracting, of economies of scope in relationship lending. They document that an important motive behind a lender's choice to engage in relationship lending is the possibility to win future business from its borrowers, in the form of additional loans, investment banking or other fee-generating services. In short, the decision to engage in relationship lending depends on the *continuation value* of a given credit relationship.

When firms experience financial distress, the likelihood of relationship termination increases because of an increased probability of borrower's default. Therefore, the likelihood of attracting future business from that borrower also decrease, and the continuation value of the credit relationship decreases as well. This implies that when borrowers are in distress relationship lending should not imply any difference in credit terms, because from a lender's perspective there is no particular additional benefit from continuing lending to a relationship borrower. The *continuation value* hypothesis has thus the following testable implications:

H2.A. In *distress*, relationship borrowers obtain *same* terms than non-relationship.

H2.B. In *normal times*, relationship borrowers obtain *better* terms than non-relationship.

Hypothesis 3: Worse Credit Terms in Distress

Lender Hold-up

Relationship lending allows lenders to acquire private, "soft" information about the borrowers. Rajan (1992), Sharpe (1990), and von Thadden (1995) present models in which borrowers cannot transfer this information to other lenders, giving inside banks' informational monopolies over the borrower. This generate an adverse selection problem for borrowers when they seek financing from outside banks because they cannot credibly signal their quality, and they have to pay higher interest rates. Informational monopolies are likely to become even larger in distress, when the borrowers has even less outside financing opportunity. The bargaining power shifts to the lender, which can exploit their market power and hold up their relationship borrowers by granting less favorable credit terms.[8]

A straightforward cross-sectional implication follows: this effect should be more pronounced in the presence of more informationally opaque borrowers, for which the transmission and accumulation of information should be relatively more important, and whose outside financing options in distress should be even more limited. The *lender hold-up* hypothesis therefore has the following predictions:

H3.A. In *distress*, relationship borrowers obtain *worse* terms than non-relationship.

H3.B. In *normal times*, relationship borrowers obtain *worse* terms than non-relationship.

H3.C. The effects are *stronger* for borrowers *with no, or little, outside financing options.*

1.3. Data and Measurement

To test and discriminate across the rich set of theoretical predictions, I construct a sample of syndicated loans matched with bank and firm characteristics. I also explicitly consider loan amendments, which in principle can be relevant in distress and for accurately measuring the strength of a credit relationship, but have been generally disregarded by most of the literature on relationship lending in the syndicated loan market. Below I describe the data sources and sample selection, discuss the measures of relationship lending, distress, and firm outside options, present the loan outcomes I will focus on in the analysis, and, and summarize the sample characteristics.

8. Diamond and Rajan (2000) also present a model in which lenders provide less or favorable terms to their borrowers depending on their relative bargaining power. However, in their model, the source of lenders' bargaining power is the presence of low bank capital, which makes banks demand immediate liquidity from their borrowers to prevent a run on deposits.

1.3.1. Data Sources and Sample Selection

I obtain information on syndicated loans from Thomson Reuters/Refinitiv Dealscan on WRDS for the time sample 1987 – 2020. Dealscan collects information on two different levels: loan packages, or deals, and loan facilities. A given package generally includes one or more loan facilities. Unless otherwise noted, I conduct my analysis at the loan facility level.[9] I limit the sample to all the loan facilities whose borrowers can be matched to Compustat using the linking table provided by Chava and Roberts (2008), and whose lenders can be matched to Compustat Bank using the linking table provided by Schwert (2018). Lenders in Dealscan are matched to the corresponding bank holding company on Compustat Bank, and in case of mergers among lenders I attribute the loans of the merging lenders to the new holding company from the time of the merge onward. The borrower linking table is updated as of mid-2017, therefore I restrict the sample up to 2016Q4.

I further require borrowers to have stock price information available on CRSP and to be incorporated in the US. Following the literature, I drop all financial firms (SIC codes 6000-6999 in Compustat). Since the focus is on borrower financial distress outside of bankruptcy, I drop all facilities whose primary purpose is described as "Debtor-in-Possession". I also drop all non-standard loans, keeping only term loans, revolvers, bridge loans, letters of credit, and other loans.[10,11] Since the main analysis of the paper focus on credit availability and pricing, I drop all the loans that have the variables *FACILITYAMT* or *ALLINDRAWN* missing on Dealscan.[12]

Most loans in Dealscan are syndicated, and therefore each loan will be associated to one or

9. WRDS has updated the Dealscan dataset starting from the summer of 2021. The update consisted in a re-organization of the entire dataset, combining all the information in a single table and changing loan identifiers. The discussion here is based on a vintage of Dealscan downloaded in August 2020, which was organized around different tables, and is now considered the "legacy" version on WRDS. In particular, I obtain and combine information from the following tables: *FACILITY, PACKAGE, LENDERSHARES, CURRFACPRICING, COMPANY, PERFORMANCEPRICING, FACILITYAMENDMENT, DEALPURPOSECOMMENT*.

10. In particular, I follow Berg, Saunders, and Steffen (2016) in classifying loan facilities as term loans or revolver lines of credit.

11. The results of the paper do not change if I restrict my analysis to term loans and revolvers only.

12. As the emphasis is on idiosyncratic borrower distress, I conduct extensive robustness tests in which I exclude all loan facilities that have a starting date during recessions, as identified by the NBER.

more lead banks, or lead arrangers, and to one or more participant lenders. In line with the literature on lending relationships, I focus only on the lead arrangers (Bharath et al., 2011; Prilmeier, 2017; Schwert, 2018). Lead arrangers are generally in charge of the active management of the loan and of the credit relationship, even if they do not retain the entirety of the loan on their balance sheets (Ivashina, 2009). To distinguish between lead arrangers and participants, I use a similar methodology to Ivashina (2009) and Bharath et al. (2011).[13] Throughout the paper, I focus mainly on loan facilities with a single lead arranger.

Finally, I merge information on loan facilities with borrower characteristics from Compustat and lender characteristics from Compustat Bank. I obtain borrower stock price information from CRSP, on borrowers' bond issuances from Mergent FISD, and on credit ratings from Capital IQ.

1.3.2. Loan Renegotiations and Amendments

I also collect information on loan renegotiations, amendments, and modifications.[14] These refer to amendments that do not result in new loan agreements – which I call loan modifications – as well as amended and restated agreements, and refinancing/rollovers of existing credit. Accounting for loan renegotiations is important. First, the presence of a loan renegotiation represents direct evidence of an active borrower-lender relationship. Second, loan amendments represent relevant credit events. When borrowers are in distress, lenders might be more likely to amend an existing loan to reflect the new circumstances rather than originate a new one. Disregarding amendments would imply forgoing an important dimension of the data. Third, it is well known that credit agreements are frequently renegotiated (Nikolaev, 2018; Roberts, 2015; Roberts & Sufi, 2009b). Since one goal of this paper is to account for the evolution of the cost of credit over time, accurately tracking renegotiations and changing

13. In particular, first I check the number of lenders. If there is only one lender, that is considered the lead arranger. In case of multiple lenders, the *LENDERSHARES* table in Dealscan has a field *LENDERROLE* that contains information on the functions performed by the various lenders. A lender that has a role as "Administrative Agent" is considered the lead arranger of the loan. If there is no administrative agent within a syndicate, then I consider lead arrangers those lenders that have one of the following title: "Agent", "Arranger", "Bookrunner", "Lead Arranger", "Lead Bank", "Lead Manager".

14. In this paper I use the terms "amendment" or "renegotiation" interchangeably.

loan terms, such as the loan spread, is crucial.

Tracking loan amendments is challenging, though. On the one hand, Dealscan keeps track of loan modifications that simply amends an existing agreement without replacing it. On the other hand, however, it generally does not distinguish between newly originated loans and amended and restated loan agreements or rollovers. I proceed as follows. First, I obtain data on loan modifications from the *FACILITYAMENDMENT* table. This contains information on loan facilities that are part of loan packages that are amended. In particular, there is information on possible changes in the loan facility amount, in the spread over LIBOR, the commitment fee, maturity, and few other terms. There are 29,185 loan facilities that are modified according to the *FACILITYAMENDMENT* table. I include in my sample the modifications to loan facilities that satisfy the above-mentioned sample selection criteria, amounting to 10,005 additional loan observations.[15]

Second, I aim to distinguish newly originated loans from amended and restated credit agreements and rollovers. To this end, I exploit the fact that Dealscan stores a significant amount of textual information in several "comment" fields.[16] A "comment" can include additional information on pricing, the syndication process, the destination of funds, and, more relevant for my purposes, if a given loan amends other loans. A typical example is represented by formulas such as *"Credit amends and restates credit agreement dated DD/MM/YYYY"*, even if the information is not *as* standardized in many instances.

To identify amended and restated credit agreement and rollovers, I use regular expressions and search for the following terms "amend", "refinanc", "replac", "restat", "extend", "repric" in the "comment" fields. This gives me a set of potential loan renegotiations and amend-

15. There are instances of reported modifications present in the *FACILITYAMENDMENT* table that do not contain observable changes to the facility-level terms reported by Dealscan in this table. From a manual examination of several of these instances, the most likely cause for their inclusion in the table is either the add-on of a facility to the corresponding loan package, or changes in package-level terms. Since the changes at the package level affect each facility, and I cannot rule out that there are unobserved changes to the facility terms, I nonetheless include these modifications in my sample, and consider them in the computation of the measures of relationship lending.

16. In particular, I focus on the *DEALPURPOSECOMMENT* field of the *DEALPURPOSECOMMENT* table, and the *COMMENT* fields of the *FACILITYAMENDMENT, DEALAMENDMENT, FACILITY,* and *PACKAGE* tables.

ments. However, there can be many false positives, and most importantly, a simple search of terms does not provide any indication as to which loans are amended. To determine which loan agreements are effectively amending other loans present in Dealscan, I develop a text-scraping algorithm that parses many pieces of information from the "comment" fields. In particular, using regular expressions, I search and parse information on dates, loan types, loan amounts. Then, I search for any loan facility in Dealscan that matches these characteristics – loan starting date, amount, loan type. If a match is found, the corresponding package is flagged as a loan renegotiation, and the amended facility is considered as not outstanding anymore beginning from the starting date of the corresponding package. I find that more than 27,000 loan packages represent a renegotiation of a previous credit agreement in Dealscan. After applying the sample selection criteria, there are 10,005 loan facilities in my sample that represent renegotiations of existing loan facilities, out of 21,039.

Using this information I construct a pseudo credit register at the loan facility-quarter level, in which I can observe which facilities are currently outstanding at any given moment in time. This allows me to observe if a loan is renegotiated in a given quarter, the loan amount available to firms over time, and which loan terms borrowers effectively face each quarter.

1.3.3. Measurement of Economic Variables

Relationship Lending

I follow previous research on relationship lending in the syndicated loan market to define the strength of the relationship between a lead bank and a borrower (Bharath et al., 2007, 2011; Li et al., 2019; Prilmeier, 2017; Schenone, 2010). One important distinction compared to previous studies is that I explicitly account for all events of loan renegotiation tracked by Dealscan when computing measures of relationship lending. As mentioned, the presence of a loan renegotiation is direct evidence of an active borrower-lender credit relationship.

I construct three measures at the loan level, for a given borrower-lender pair. The main one captures the strength of the credit relationship at the intensive margin. In particular, *Relationship* is defined as the fraction of the number of new loans or loan amendments the borrower obtained from the current lender over the total number of loans and loan amendments obtained from any lender over a five-year window preceding the current loan event – which could be a new loan or a renegotiation itself.

$$
\begin{aligned}
&\textit{Relationship}_{b,f,t} \\
&\qquad = \frac{\text{Number of new loans/renegotiations between bank } b \text{ and firm } f \text{ from } t-5 \text{ to } t}{\text{Total number of new loans/renegotiations by firm } f \text{ from } t-5 \text{ to } t}
\end{aligned}
$$

The other two are defined as follows. The first, *Relationship ($ Amt)* is similarly defined as the fraction of the amount of credit the borrower obtained from the current lender over the total credit granted by any lenders over the 5-year window preceding the current loan. Intuitively, this measure weights the number of interactions between borrowers and lenders by the loan facility amount.

$$
\textit{Relationship (\$ Amt)}_{b,f,t} = \frac{\text{Amount of credit from bank } b \text{ to firm } f \text{ from } t-5 \text{ to } t}{\text{Total amount of credit obtained by firm } f \text{ from } t-5 \text{ to } t}
$$

The second, $\mathbb{I}(REL)$, captures the extensive margin, and the extent to which a credit relationship is still ongoing over time. It is a dummy variable that takes value 1 if the lender and borrower entered a credit agreement or a renegotiation in the 5 years preceding the current loan and 0 if the borrower entered any credit relationship in the same 5-year window, but not with the same lender of the current loan.

Following Bharath et al. (2011) I require the presence of at least one new loan or loan renegotiation in the five-year window preceding a given loan for the measures of relationship lending to be defined. If this condition is not met, the relationship measures are set to missing for that loan, which is thus excluded from the sample.[17] Also, in the presence of multiple lead arrangers, I define each variable as the maximum value of each variable over the individual borrower-lender pairs.

17. See Bharath et al. (2011, footnote 11, pag. 1153).

Financial Distress

To measure financial distress, I employ an estimate of borrower default probability based on the Merton model of credit risk (Merton, 1974). This is likely to capture the actual indicator lenders use to assess their own borrowers' credit status, as the Merton model represents the foundation underlying a leading industry measure of credit risk, the proprietary Moody's KMV EDF.

In particular, a firm is considered in distress in a given month if during the preceding 12-month period its expected default probability (EDF) is in the top quartile of the distribution of monthly EDFs for 6 or more months, following an approach similar to Li et al. (2019). The EDF is computed employing the "naive" approach described by Bharath and Shumway (2008), which has the desirable property of performing similarly to the measure computed using the original approach of Merton (1974) in predicting firm default, with lower computational requirements regarding numerical estimation. Specifically, following Bharath and Shumway (2008), the EDF is defined for each firm-month pair as follows:

$$EDF = \mathcal{N}\left(-\frac{\ln[(E+D)/D] + \left(r - 0.5\sigma_V^2\right)T}{\sigma_V\sqrt{T}}\right)$$

in which $\mathcal{N}(\cdot)$ is the cumulative standard normal distribution function, E is the market value of the firm's equity, F is the face value of the firm's debt, r is the firm's stock return over the previous 12-month period, $\sigma_V = [E/(E+F)]\sigma_E + [F/(E+F)](0.05 + 0.25\sigma_E)$, and σ_E is the volatility of the firm's equity estimated using daily stock returns data over the previous 12 months (Bharath & Shumway, 2008).

In particular, I compute the EDF for each firm in the universe of the CRSP/Compustat database at the monthly level over the full time sample under consideration (1986-2016). I then consider the 75th percentile of the resulting distribution as the threshold above which a firm can be considered in distress.[18] The resulting variable is a dummy $\mathbb{1}(\textit{Distress})$ that

18. In robustness tests I also consider the 70th, 80th, and 90th percentiles of the same distribution as thresholds, as well as the Altman Z-Score as an alternative measure of firm distress.

takes value 1 for a given firm-month if the number of months in which its monthly EDF is in the top quartile of the distribution of all firm-months is equal or greater than six. Note that the distribution is not limited to the firm-months associated with the loan facilities satisfying the sample selection criteria described in Section 1.3.1.

Firms' Outside Options

Borrowers" outside options play an important role in theories of relationship lending. To measure firms' outside options I use three proxies. The first proxy is the access to public bond markets. Firms that issue bonds are likely to have a broader menu of financing options, and more public information available to market participants through the market price of their bonds and the analysis of their underwriters (Hale & Santos, 2009; Santos & Winton, 2008). I therefore classify firms as either bond issuers or not depending on whether they ever issued a public bond. Formally, I define $\mathbb{I}(PBOND)$, which takes value 1 if the firm has ever issued a public bond before taking out a loan and 0 otherwise.[19]

A potential issue with this proxy is the possibility that a firm issued a public bond a long time before taking out a loan, and therefore it might have lost access to the public bond market, or that the public information thereby generated about the firm does not accurately reflect the underlying condition of the firm anymore. To address this concern, I also consider whether firms recently issued a public bond or not a second proxy. The idea is to capture the degree of availability of recent public information about a firm. Formally, I define $\mathbb{I}(PBOND3Y)$, which is a dummy variable that takes value 1 if the firm has issued at least one public bond in the three years preceding a loan, following Santos and Winton (2019). To capture access to the bond market in general, either public or private, I also define the variable $\mathbb{I}(BOND)$, which takes value 1 if the firm has ever issues a bond, either as a private placement or on public debt markets.

19. In principle I would like to observe whether a firm has the possibility of issuing a public bond even in absence of an actual issuance, but this is obviously not available to a researcher.

Loan Outcomes

To study if relationship lending is beneficial to borrowers when they experience idiosyncratic financial distress, I consider several loan outcomes. Loans are multi-dimensional objects and to fully characterize the implications for borrowers it is important to keep a holistic approach. The first one is the quantity of credit available to borrowers, defined as "Log(Loan Amount)". This is meant to capture benefits at the extensive margin, and either corresponds to the loan facility amount at origination or the quantity of credit that is observed as a result of an amendment or modification. As described in Section 1.3.2, I track the credit amount available to firms by assuming that the loan is outstanding until maturity or is amended by another loan agreement or modification.

The second one is the cost of credit, which is the focus of most theoretical work. Following the vast majority of empirical literature, I use the "All-In Drawn Spread" (AISD) as the baseline measure of cost. This captures the cost of the drawn part of the credit, being calculated as the sum of the loan spread over LIBOR and the annual facility fee. I also consider the "All-In Undrawn Spread" (AIUD), which measures the cost on the undrawn, but committed, part of credit, being calculated as the sum of the annual facility fee and the commitment fee.

I track the cost of credit over the lifetime of a loan by explicitly accounting for loan modifications and the performance pricing (PP) grids embedded in loan contracts. Each loan modification contains information on the updated spread over LIBOR and the commitment fee. Each PP grid specifies a step-wise function that maps the the level of certain accounting variables or the borrower's credit rating to the level of the spread over LIBOR, the annual fee, the commitment fee, and other fees.[20] In particular, the vast majority of the PP grids tie the cost of credit to either the Debt-to-EBITDA ("Total Debt to Cash Flow" in Dealscan) ratio (43 %) or to the credit rating assigned by S&P (30 %).[21] To infer the cost of a loan through time, I obtain for each firm-quarter the value of the relevant underlying accounting variables from

20. Information on PP grids can be found in the *PERFORMANCEPRICING* table in Dealscan.
21. Other commonly used variables include: Leverage (6%), Senior Debt to EBITDA (3%), Maturity (3%), Interest Coverage Ratio (2%), etc. . Also see: Adam and Streitz (2016); Asquith et al. (2005).

Compustat, such as the Debt-to-EBITDA ratio. Then, I check to which "step" in the PP grid this value falls. I then assign to that loan-quarter pair the loan spread or the fee specified by that "step" in the PP grid. I do this for all the loans with a single PP grid, and whose PP grid is specified on the credit rating or the accounting variables that I can reasonably map to a variable that can be computed using the quarterly version of Compustat.

The other two outcomes I consider are given by the likelihood of collateral requirements and the level of upfront fees. The presence of collateral requirements is an important aspect of the financing process, as during distress borrowers could experience a deterioration in the market/resale value of their pledgeable assets. To measure this aspect, I define the variable $\mathbb{I}(Collateral)$, which takes value 1 if the *SECURED* variable in Dealscan is equal to "Yes" and 0 if the same variable is equal to "No". Upfront fees are the fees paid by the borrower at the moment of loan originations, and represent an additional margin of loan pricing. To measure them, I consider the related variable on Dealscan.

1.3.4. Sample Characteristics

The final sample contains 31,619 loan observations, including 21,039 loans that appear as new loans in Dealscan, and 10,580 observations that appear as loan modifications. According to my analysis, of those 21,039 loan observations, 10,005 represent instances of renegotiations – either as amendments, restatements, or refinancing. Table A.1 describes the variables used in the analysis, Table A.2 presents the sample characteristics of the loan events present in the sample, as well as the borrower and lender characteristics.

1.4. Empirical Analysis

In this section I perform an empirical analysis on the hypotheses discussed in Section 1.2. I start by presenting evidence on the use of performance pricing and likelihood of loan modification that motivates the use of a pseudo credit register in lieu of the standard dataset based on loan events only. I then document that relationship lending provide benefits to borrowers in distress in the form of higher credit availability and lower spreads on the drawn amount of credit. This effect is not compensated by an increase in the fees on the undrawn credit amount, by an increased likelihood to require collateral or by increased upfront fees. This evidence is consistent with the hypotheses predicting relationship lending providing favorable terms in distress. To discriminate among different possible explanations and better understand the underlying economic mechanisms, I repeat the analysis over subsamples of borrowers differing in their outside financing options. I show that firms benefit from relationship lenders irrespectively of their outside financing options, providing support to theories emphasizing implicit commitment and reputational capital. However, the benefits vary qualitatively across firms: firms with access to public debt markets benefit mainly in terms of credit quantity, firms without benefit mainly from pricing terms.

1.4.1. The Need for a Pseudo Credit Register

As described in Sections 1.3.2 and 1.3.3, I construct a pseudo credit register that tracks loan availability and loan pricing over time to overcome two related issues. The first issue arises because loans are frequently renegotiated (Nikolaev, 2018; Roberts, 2015; Roberts & Sufi, 2009b). This implies that loan terms and conditions changes even in absence of a new loan origination. The second issue emerges because a large fraction of loan contracts include performance pricing grids, which tie the cost of credit – including the loan spread and various fees – to the underlying borrowers' performance. Therefore, the cost of credit a firm faces may vary even in absence of a new loan origination or a loan amendment.

Moreover, the presence of a performance pricing grid in credit agreements reduces the probability that the loan will be renegotiated (Asquith et al., 2005; Nikolaev, 2018). In other words, the presence of performance pricing provisions reduces the occurrence of loan events that are observable by the researcher, even if the cost of credit is potentially changing. This issue is relevant because I show that that relationship lending is negatively correlated with the use of performance pricing provisions. In particular, Table A.3 shows that relationship lenders are less likely to include a performance pricing grid by 3.5%. This is consistent with the results of (Adam & Streitz, 2016). The implication of these evidence taken together implies that failing to account for changing credit terms would give rise to a measurement bias. Hence, I conduct my regression analyses using this pseudo credit register to alleviate these issues.

In the next section I turn to the description of the empirical approach.

1.4.2. The Effect of Relationship Lending during Borrower Distress

Theories of relationship lending has several implications for loan outcomes in normal times, in distress, and across different types of borrowers. Here I focus on the first two aspects, examining later the predictions about heterogeneity in the cross section. I start by regressing several loan outcomes on measures of relationship lending, distress, and their interaction term.

$$\begin{aligned} \textit{Loan Outcome}_{b,f,t} = \alpha_f + \alpha_b + \alpha_t + \beta_D \cdot \mathbb{I}(\textit{Distress})_{f,t-1} + \beta_R \cdot \textit{Relationship}_{b,f,t} \\ + \beta_{RD} \cdot \textit{Relationship}_{b,f,t} * \mathbb{I}(\textit{Distress})_{f,t-1} + \gamma \cdot X_{b,f,t-1} + \varepsilon_{b,f,t} \end{aligned} \tag{1.1}$$

The dependent variable $\textit{Loan Outcome}_{b,f,t}$ represents different loan outcomes that aim to holistically capture several aspects of the credit relationship. In particular, I use the following as dependent variable: i) "Log(Loan Amount)" to investigate the effects of relationship lending on borrowers' credit availability; ii) "All-In Drawn Spread" and "All-In Undrawn Spread" to study the implications on the cost of credit; iii) $\mathbb{I}(\textit{Collateral})$ to understand the effects on collateral requirements; iv) "Upfront Fee" to obtain insights on an additional dimension of loan pricing.[22]

The main independent variables are $\mathbb{I}(\textit{Distress})_{f,t-1}$, defined in Section 1.3.3 and computed monthly for each firm in the sample, $\textit{Relationship}_{b,f,t}$, which is one of the three measures of relationship lending defined at the loan level in Section 1.3.3, and their interaction term. β_D captures the difference between non-relationship loans in normal times and in distress,

22. I conduct the baseline analysis for the first outcomes terms using the pseudo credit register I assembled because I can observe changes due to loan modifications or to performance pricing grids. I conduct the analysis for the collateral and the upfront fee at the loan origination level only because I cannot observe variations in these terms over time.

β_R captures the difference between relationship loans and non-relationship loans in normal times, and β_{RD} measures the difference between relationship loans in normal times and in distress.

The key economic object of interest is the difference between relationship loan outcomes in distress and non-relationship loan outcomes in distress, which is given by the sum of $\beta_R + \beta_{RD}$. A positive coefficient for the analysis on the cost of credit and collateral requirement will be interpreted as evidence of worse credit terms in distress. Viceversa, a negative coefficient for the analysis on the cost of credit and collateral requirement will be interpreted as evidence of better credit terms in distress. A zero coefficient will be interpreted as evidence of same credit terms in distress. This is the main focus of the paper. However, to fully discriminate among different theories, the coefficients β_R and β_{RD} considered separately might also be important, and will also be discussed.

In all regressions, I include year-quarter fixed effects to control for changing macroeconomic conditions and account for potentially different moments in the business cycle.[23] I control for a series of firm characteristics, such as credit rating dummies, size, leverage, profitability, cash-flow, liquidity, tangibility, firm age, investment opportunities, to alleviate the impact of omitted variables that could be correlated with the relationship status and the outcomes of interest. To account for the non-random matching between banks and firms, I include borrower fixed effects and lender fixed effects, which control for unobserved heterogeneity at the firm and bank level that could drive the matching. I also include bank size and bank capital; the latter represents an important time-varying driver of bank-firm matching, as documented by Schwert (2018). Lender fixed effects are also important to control for potential heterogeneous bank business models – i.e. transactional vs relationship lending – that could be correlated with both loan outcomes and relationship status. Finally, I also control for loan-level characteristics, such as loan purpose, loan type, the presence of a performance pricing grid, and the number of lenders in the syndicate.

23. Note that, as mentioned in Section 1.3.1, I drop all loan observations that occur during a NBER recession.

Results

The results of the analysis are reported in Table A.4 and Table A.5. Relationship lending implies higher credit availability in distress, lower spreads on the drawn credit, no higher fees on the undrawn credit or to be paid upfront, and no higher collateral requirements.

I first examine the impact of relationship lending on the amount of credit made available to the borrowers. This a natural outcome to look at since when a borrower is in distress is likely to experience higher liquidity needs than normal times, and likely represent the most relevant dimension of a credit relationship. Table A.4 presents the results in columns 1 and 2, obtained from a regression following the specification described in Equation (1.1). The estimates for the net effect of relationship lending in distress are both economically and statistically significant, and are relatively similar across specifications with and without lender fixed effects. To interpret the estimates, a back-of-the-envelope calculation implies that a one standard-deviation increase in the measure of relationship lending implies a higher credit availability for borrowers in distress by approximately $18M for the average loan.

I then proceed to examine the implications of relationship lending on the cost of credit, using two measures. The first one is the cost of drawn credit, given by the All-In Drawn Spread, which is the focus of the great majority of the extant empirical and theoretical literature on relationship lending. The second one is the cost of undrawn credit, given by the All-In Undrawn Spread. Columns 3 and 4 of Table A.4 report the results of the analysis for the All-In Drawn Spread. Lenders charge their relationship borrowers with lower interest rates spread when in distress. The estimates are again economically and statistically significant. A one standard-deviation increase in the measure of relationship lending implies a lower All-In Dawn Spread by 4 basis points, which represent a saving up to $600,000 dollars over the lifetime of the average loan. Columns 5 and 6 report the estimates for the effect on the All-In Undrawn Spread, which are not statistically different from zero. Importantly, these estimates imply that the benefits in terms of higher credit availability and lower spreads are not compensated by a higher fee on the committed, undrawn amounts.

Finally, I examine if in exchange for these benefits lenders are more likely to require collateral or charge higher upfront fees to their relationship borrowers. The results of the analysis for these two variables are reported, respectively, in columns 1 and 2, and 3 and 4 of Table A.5. The evidence strongly rules out that lenders require higher collateral, as the point estimates are negative, though indistinguishable from zero. The coefficients on the upfront fees are positive, yet statistically insignificant. This could be due to the low power of the test given the low number of non-missing observation of the corresponding variable in Dealscan. The positive coefficient suggests that lenders might use higher upfront fees to compensate for the insurance provision in distress, but the limited number of observation does not allow to properly test this hypothesis.

Overall, the evidence points to a beneficial effect of relationship lending when borrowers are in distress, which rules out the *continuation value* and the *lender hold-up* hypotheses, and provides support to theories that posits insurance provisions in distress.

Robustness Tests

The evidence is robust to a series of robustness tests. Table A.6 shows that the main results are robust to employing the alternative measures of relationship lending presented in Section 1.3.3. Table A.7 presents the results of the main analysis augmenting the baseline specification with borrower×time and lender×time fixed effects. The effects of relationship lending continue to be economically and statistically significant. This alleviates concerns that differential firm demand or differential bank supply drive the observed effects. Table A.8 shows that the results are not sensitive to the specific definition of distress employed in the main analysis. Specifically, repeating the analysis using different thresholds (70th, 80th, and 90th percentile) or the Altman Z-Score (Altman, 1968) to define distress does not change the results of the analysis.[24] Table A.9 confirms the main results over the larger sample that

24. The estimate for the net effect of relationship lending on the All-In Drawn Spread when using the 90th percentile to define distress and lender fixed effects is not statistically significant at any conventional values—the p-value, unreported, is 0.109. This could be due to either a lower within-bank variation in the measure of relationship lending given the lower number of observations in distress due to the higher threshold, or reflect a weakening of the effect of relationship lending as the distress gets more severe. However, the relatively similar estimates on the net effect of relationship lending on loan amounts and pricing terms make the former explanation more likely.

includes also loans with multiple lead arrangers.

While the pseudo credit register I assembled has several advantages over a standard dataset that includes only terms observed in the presence of a loan event, there is a concern that measurement error in tracking loan renegotiations and credit terms over time could drive my results. Measurement error could arise from prepayment of loans or unobserved amortized repayment over time, for example. To alleviate the concern that measurement error in tracking credit terms over time is the driving factor behind my results, I perform two tests. First, I repeat my analysis only using observations corresponding to the quarters in which I observe a loan origination or renegotiation. Table A.10 reports the results of this exercise, and the economic message is unchanged. Relationship lending is beneficial for borrowers in distress. Secon, I repeat my analysis for the stand-alone pricing terms that are actually specified in the performance pricing grids, without further aggregations that could imply measurement error in the All-In Drawn and Undrawn spreads. The estimates displayed in Table A.11 confirm the baseline results.

1.4.3. The Role of Borrowers' Outside Options

The evidence presented in the previous section appears to align most closely with theories of implicit commitment and reputational capital in lending relationships. However, to fully discriminate among the different theories that predict benefits for relationship borrowers in distress, I now examine whether, and how, the effect of relationship lending varies depending on borrowers' outside financing options. These play a key role in theories of relationship lending because they are closely related to the degree of available public information about the borrower, and they determine the relative bargaining power in the credit relationship.

I repeat my analysis for the main three loan outcomes over subsamples of borrowers reasonably characterized by different degrees of outside financing options and informational opacity, using the different measures described in Section 1.3.3. In particular, the one I consider more economically relevant is whether a firm has access to public bond markets. Table A.12 and Table A.13 present the results of the subsample analysis. Overall, borrowers with access to bond financing experiences benefits mainly in the form of higher credit availability, whereas borrowers without benefit mainly from lower interest rate spreads on drawn credit. These benefits are not compensated by a higher All-In Undrawn Spread for either group of firms.

Despite being qualitatively different, the benefits of relationship lending accrue to borrowers irrespectively of their outside financing options. These results are in line with the theories of *implicit commitment & reputational capital*, in which banks offer better terms to borrowers and keep offering those terms even in distress to develop a reputation that in turn should allow them to win future business.

1.5. Conclusion

In this paper I study whether relationship lending can help borrowers mitigate the costs of idiosyncratic financial distress, which can be sizable. I first present the empirical challenge presented by the differential use of performance pricing grids in loan contracts by relationship lenders and non-relationship lenders, and by how that affects the loan events that can be actually observed in a "standard" dataset. To address these issues, I construct a novel dataset that results into a pseudo credit register that track credit quantity and price over time, by accounting for loan amendments and modifications and for state-contingent loan pricing provisions. I then use this dataset to compare the credit terms by relationship lenders and non-relationship lenders in distress, employing a within-firm approach. By employing a measure of relationship lending that accounts for loan modifications – a novelty in the literature – I find strong evidence of lenders providing favorable terms to their relationship borrowers in distress, in the form of higher credit amount and lower interest rate spreads. These benefits are qualitatively different in the cross section of borrowers' outside options. In contrast with the findings of Li et al. (2019), I provide evidence supporting theories of implicit commitment and reputational capital.

CHAPTER 2

BANK SPECIALIZATION AND THE DESIGN OF LOAN CONTRACTS

(with Stefano Pietrosanti)

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.[25] 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.[26]

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.[27] 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

25. Berger and DeYoung (2001); Carey, Post, and Sharpe (1998); Hughes, Lang, Mester, and Moon (1996); Paravisini, Rappoport, and Schnabl (2017).
26. On the relation between bank portfolio concentration and related performances, see Acharya, Hasan, and Saunders (2006); Beck, De Jonghe, and Mulier (2022); Boeve, Duellmann, and Pfingsten (2010); "Does Diversification Improve the Performance of German Banks? Evidence from Individual Bank Loan Portfolios" (2007); Tabak, Fazio, and Cajueiro (2011). On the real effects of bank specialization, see De Jonghe, Dewachter, Mulier, Ongena, and Schepens (2020); Gopal (2021); Paravisini et al. (2017); Schwert (2018).
27. 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.

market.[28] 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 the theoretical framework by Gârleanu and Zwiebel (2009), who argue 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.[29] 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 in 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:

28. U.S. syndicated lending topples records in 2017, Reuters, December 2017.

29. We choose this sample period because coverage of the syndicated loan market sharply improves in Dealscan after 1995 (Chava & Roberts, 2008).

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).[30] 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).[31] Looking at both is important as these contract terms are jointly determined, and there 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 the argument 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

30. This measure is similar to the one developed by Murfin (2012).
31. The AISD is a fee paid over the base rate (usually LIBOR) for each dollar of credit drawn.

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 et al. (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.[32] 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 (2022) 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

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

triggering potentially costly defaults or renegotiations, and could represent a different economic mechanism that would explain our results.[33] We show that this is not the case, and find that banks with high market shares 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.

The paper proceeds as follows. In Section 2.1 we review the related literature and highlight the contribution of this paper. In Section 2.2 we describe the sample construction, discuss how we measure specialization, and provide evidence on bank specialization in the syndicated loan market. In Section 2.3 we present our empirical strategy, our findings, and discuss several alternative explanations. In Section 2.4 we provide concluding remarks.

2.1. Related Literature and Contribution

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 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 (2021) document the role of lender specialization in collateral, and how this matters for lending de-

33. 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).

cisions 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 et al. (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.

2.2. 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.

2.2.1. 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.[34] We also merge firm characteristics in Compustat with the industry classification developed by Hoberg and Phillips (2010, 2016), which is available for most public companies present in Compustat starting from 1987.

We obtain information on banks by matching lenders in Dealscan with bank characteristics,

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

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.[35] 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).[36] We identify a lead arranger following the procedure outlined in Chakraborty et al. (2018).[37]

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).[38] 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.

The unit of observation in Dealscan is a loan facility. However, information on loan covenants

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35. See, for example, Chakraborty, Goldstein, and MacKinlay (2018); Prilmeier (2017); Schwert (2018).
36. If there are multiple lead arrangers, we split the loan amount equally among them.
37. 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 et al. (2007, 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)
38. 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.

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.

2.2.2. Two Measures of Bank Specialization

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.[39] The *HHI* of the commercial lending portfolio of a given bank is defined as follows:

$$HHI_{b,t} = \sum_{i=1}^{I} L_{i,b,t}^2 \tag{2.1}$$

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

39. 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:

$$\overline{HHI}_{b,t} = \sum_{b=1}^{B} \frac{L_{b,t}}{L_t} \left(\sum_{i=1}^{I} L_{i,b,t}^2 \right) \tag{2.2}$$

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:

$$HHI_{M,t} = \sum_{i=1}^{I} L_{i,t}^2 \tag{2.3}$$

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:

$$Spec_{i,b,t} = \begin{cases} 1 & \text{if } L_{i,b,t} \geq L_{it}^* \\ 0 & \text{otherwise} \end{cases} \tag{2.4}$$

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 A.2 presents some simple examples involving two banks and an economy with only two 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.

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.[40] 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 A.3, we plot the

40. 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.

HHI of the commercial lending portfolio for the average bank computed for each quarter as in Equation (2.1), and the same measure computed for the market portfolio as in Equation (2.3). 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 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 A.4 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 A.5 we plot the autocorrelation of $Spec_{it}^{b}$ defined in Equation (2.4), 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.

2.2.3. Measurement of Economic Variables

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).[41]

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 vice versa (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.

41. 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.

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 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.[42] 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 A.14.

42. 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.

2.2.4. Sample Characteristics

Table A.15 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 2.2.1. 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 A.15 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 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 A.15 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+.[43] 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 A.15 reports information on the lenders in our samples. The Strictness Sample includes 2,093 bank-quarter observations for 95 banks. The average

43. 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.

bank is large, with \$200 billion in total assets, a deposit to asset ratio of 60%, with book equity capital amounting to 7%.

2.3. Empirical Analysis

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.

2.3.1. 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 (2.4), is equal to 1 and the firm f belongs to industry i. The top panel of Table A.16 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 A.16 displays the results of the t-tests for firm characteristics.[44] 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 A.16 shows the estimate of t-tests on bank characteristics.[45] 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, with a similar ratio of non-performing assets.

Overall, the evidence in Table A.16 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.

2.3.2. 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 lend-

44. 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.

45. Since the same bank issue more than one loan, the standard errors for the t statistics in Table A.16 have been adjusted for clustering at the bank level.

ing 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 A.16 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.[46]

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.[47]

Formally, we employ the following specification:

$$\begin{aligned} \textit{Loan Contract Term}_{f,b,t} = \theta_{b,t} + \textit{Other Fixed Effects} + \beta \cdot \textit{Specialization}_{f,b,t-1} \\ + \gamma_F \cdot \textit{Firm Controls}_{f,t} + \gamma_L \cdot \textit{Loan Controls}_{f,b,t} + \varepsilon_{f,b,t} \end{aligned} \tag{2.5}$$

46. 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).

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

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 $Spec_{it}^{b}$ (defined in Equation (2.4)). *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.[48] 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.[49]

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

49. 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 2.3.6. Finally, we note that the same choice of rolling window length, performed for similar reason, can also be found in Paravisini et al. (2017).

2.3.3. The Effect of Specialization on Loan Covenant Strictness and Pricing

We now introduce the baseline results of our analysis. Table A.17 reports the regression estimates of the specification in Equation (2.5) 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.

2.3.4. Assessing Alternative Explanations

There might be alternative explanations for the results presented in Table A.17. 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 2.2, which are meant to capture different aspects of relationship lending. Table A.18 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 2.2, 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 A.19 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), whereas 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 A.20 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.

2.3.5. 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 (2.5), with the inclusion of interaction terms between the specialization variable and the number of defaults on lender portfolio, as follows:

$$Loan\ Term_{f,b,t} = \theta_{b,t} + \theta_f + \rho \cdot Specialization_{f,b,t-1} \times Defaults_{b,t-1} \\ + \beta \cdot Specialization_{f,b,t-1} + \gamma_D \cdot Defaults_{b,t-1} + \gamma \cdot X_{f,b,t} + \varepsilon_{f,b,t} \tag{2.6}$$

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 A.21 shows the results of regressions as in Equation (2.6), 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.

2.3.6. 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 A.22. Second, computing the specialization measures starting from 1996 instead of 1987 leaves the results virtually unchanged; the estimates are presented in Table A.23. 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 A.24. 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, 2022).

Finally, averaging the specialization dummy defined in Equation (2.5) over different time horizons does not change the main message of the paper. As can be seen in Table A.25, 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.

2.4. 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).

APPENDIX

Tables and Figures

A.1. Tables

Table A.1. Variable definitions

Variable Name	Definition	Data Source
Borrower		
Ln(Assets)	Ln(`atq`)	Compustat
Book Leverage	(`dlttq` + `dlcq`)/`atq`	Compustat
Liquidity	`cheq`/`atq`	Compustat
Profitability	`oibdpq`/`atq`	Compustat
Cash Flows	$\text{Ln}\left[1+\frac{\text{rolling 4-qtr sum of } \texttt{oibdpq}}{\texttt{dlttq} + \texttt{dlcq}}\right]$	Compustat
Tangibility	`ppentq`/`atq`	Compustat
Market-to-Book	(`prccq × cshoq + atq - ceqq`)/`atq`	Compustat
$\mathbb{I}$(Credit Rating)	Equal to 1 if `ltrf = 1`, 0 otherwise	Capital IQ
EDF	Described in Section 1.3.3	CRSP/Compustat
Years since IPO	Current date minus first date in Compustat	Compustat
$\mathbb{I}(PBOND)$	Described in Section 1.3.3	Mergent FISD
$\mathbb{I}(PBOND3Y)$	Described in Section 1.3.3	Mergent FISD
Loan		
Relationship	Described in Section 1.3.3	Dealscan
Relationship ($ Amt)	Described in Section 1.3.3	Dealscan
$\mathbb{I}(REL)$	Described in Section 1.3.3	Dealscan
Loan Amount ($M)	`facilityamt/1e6`	Dealscan
Loan Spread	Fee (over Libor) charged per $ of drawn credit (`fac_maxbps`)	Dealscan
Commitment Fee	Fee charged per $ of undrawn credit (`commitment`)	Dealscan
Annual Fee	Fee charged annually per total credit amount (`annual_fee`)	Dealscan
AISD	Loan Spread + Annual Fee	Dealscan
AIUD	Commitment Fee + Annual Fee	Dealscan
Maturity (Months)	`maturity`	Dealscan
$\mathbb{I}$(Collateral)	Equal to 1 if `secured` = "Yes", 0 otherwise	Dealscan
Upfront Fee	One-time fee paid to lenders (`upfront_fee`)	Dealscan
N. Lenders	N. syndicate members	Dealscan
$\mathbb{I}$(PP)	Equal to 1 if loan includes perf. pricing grid (PP), 0 otherwise	Dealscan
$\mathbb{I}$(PP - Pred. Decr.)	Equal to 1 if loan spread closer to PP max spread than min	Dealscan
$\mathbb{I}$(PP - Pred. Incr.)	Equal to 1 if loan spread closer to PP min spread than max	Dealscan
$\mathbb{I}$(Revolver)	Equal to 1 if loan is a revolver (Berg et al., 2016, see p.1382)	Dealscan
$\mathbb{I}$(Term Loan)	Equal to 1 if loan is a term loan (Berg et al., 2016, see p.1382)	Dealscan
$\mathbb{I}$(Corp. Purposes)	Equal to 1 if `primarypurpose` = "Corp. Purposes"	Dealscan
$\mathbb{I}$(Debt Repay.)	Equal to 1 if `primarypurpose` = "Debt Repay."	Dealscan
$\mathbb{I}$(Work. Capital)	Equal to 1 if `primarypurpose` = "Work. Capital"	Dealscan
$\mathbb{I}$(Takeover)	Equal to 1 if `primarypurpose` = "Takeover"	Dealscan
Lender		
Ln(Bank Assets)	Ln(`atq`)	Compustat
Bank Capital (Book)	`ceqq`/`atq` × 100	Compustat
Bank Capital (Mkt)	(`prccq × cshoq`)/(`atq - ceqq+ prccq × cshoq`) × 100	Compustat

Table A.2. Descriptive statistics

	Mean	S.D.	25^{th} pct	Median	75^{th} pct	Unique Obs.
Borrower Characteristics (Unique Borrowers: 3,076)						
Ln(Assets)	7.12	1.69	5.95	7.07	8.25	19,178
Book Leverage	0.33	0.20	0.20	0.31	0.43	19,178
Liquidity	0.07	0.09	0.01	0.03	0.08	19,178
Profitability	0.03	0.03	0.02	0.03	0.05	19,178
Cash Flows	0.49	0.60	0.20	0.33	0.55	19,178
Tangibility	0.35	0.25	0.14	0.28	0.54	19,178
Market-to-Book	1.63	0.81	1.12	1.39	1.85	19,178
$\mathbb{I}$(Credit Rating)	0.50	0.50	0.00	0.00	1.00	19,178
EDF	0.07	0.19	0.00	0.00	0.01	18,454
Years since IPO	20.18	16.41	6.64	15.21	31.73	19,178
$\mathbb{I}(PBOND)$	0.49	0.50	0.00	0.00	1.00	19,178
$\mathbb{I}(PBOND3Y)$	0.32	0.47	0.00	0.00	1.00	19,178
Loan Characteristics (Unique Loans: 21,039 – Modifications: 10,580)						
Relationship	0.65	0.38	0.33	0.75	1.00	31,619
Relationship ($ Amt)	0.69	0.38	0.38	0.90	1.00	31,619
$\mathbb{I}(REL)$	0.85	0.35	1.00	1.00	1.00	31,619
Loan Amount ($M)	354.35	524.66	55.00	165.00	400.00	31,619
All-In Drawn Spread	207.57	125.01	120.00	200.00	275.00	31,619
Maturity (Months)	45.35	21.95	29.00	48.00	60.00	30,981
All-In Undrawn Spread	32.02	21.58	15.00	27.50	50.00	19,351
$\mathbb{I}$(Collateral)	0.71	0.45	0.00	1.00	1.00	14,964
Upfront Fee	8.42	27.38	0.00	0.00	0.00	19,422
N. Lenders	8.80	8.47	3.00	7.00	12.00	21,039
$\mathbb{I}$(PP)	0.47	0.50	0.00	0.00	1.00	21,039
$\mathbb{I}$(PP - Pred. Decr.)	0.21	0.41	0.00	0.00	0.00	21,039
$\mathbb{I}$(PP - Pred. Incr.)	0.25	0.43	0.00	0.00	1.00	21,039
$\mathbb{I}$(Revolver)	0.69	0.46	0.00	1.00	1.00	21,039
$\mathbb{I}$(Term Loan)	0.28	0.45	0.00	0.00	1.00	21,039
$\mathbb{I}$(Corp. Purposes)	0.42	0.49	0.00	0.00	1.00	21,039
$\mathbb{I}$(Debt Repayment)	0.14	0.35	0.00	0.00	0.00	21,039
$\mathbb{I}$(Work. Capital)	0.15	0.36	0.00	0.00	0.00	21,039
$\mathbb{I}$(Takeover)	0.11	0.31	0.00	0.00	0.00	21,039
Lender Characteristics (Unique Lenders: 96)						
Ln(Bank Assets)	12.28	1.52	11.19	12.33	13.51	3,130
Bank Capital (Book, %)	7.33	2.67	5.25	7.59	9.10	3,130
Bank Capital (Mkt, %)	12.12	6.19	7.41	11.50	15.97	2,946

Table A.3. The effect of relationship lending on the use of performance pricing provisions

This table reports the estimates of the coefficients from the following regression over the sample of loan observations from the Dealscan main table, not including the loan modifications:

$$\mathbb{I}(PP)_{b,f,t} = \alpha_f + \alpha_b + \alpha_t + \beta \cdot Relationship_{b,f,t} + \gamma \cdot X_{b,f,t-1} + \varepsilon_{b,f,t}$$

in which $\mathbb{I}(PP)_{b,f,t}$ is a dummy that takes value 1 if a loan granted by lender b to borrower f at time t specifies a performance pricing grid. $\alpha_f, \alpha_b, \alpha_t$ represent, respectively, borrower, lender, and year-quarter fixed effects. $Relationship_{b,f,t}$ is the fraction of loan events between lender b and borrower f over the total loan events of firm f occurred in the 5 years preceding the given loan observation. $X_{b,f,t-1}$ is a vector of borrower, loan, and lender controls. Borrower controls include: credit rating dummies, size, book leverage, profitability, years since IPO, tangibility, liquidity, cash flows, market-to-book, dummy for issuance of any bond. Loan controls include dummies for loan types and loan purpose, and the number of syndicate participants. Lender controls include size and book equity. These controls are always included in the specifications. In parentheses t statistics are reported, obtained from clustering standard errors at the borrower level. ***, **, * indicate statistical significance at the 1%, 5% and 10%, respectively.

	Dependent Variable: $\mathbb{I}$(PP)	
	(1)	(2)
Relationship	$-.0351^{***}$	$-.0382^{***}$
	(-2.76)	(-2.95)
Borrower FE & Year-Qtr FE	Yes	Yes
Lender FE	–	Yes
Adj. R Sq.	.365	.372
Obs.	19,946	19,942

Table A.4. The effect of relationship lending on loan amount and pricing in distress

This table reports the estimates of the coefficients from the following regression over the loan-quarter level sample, in which only loan facilities with a single lead arranger are included:

$$\textit{Loan Outcome}_{b,f,t} = \alpha_f + \alpha_b + \alpha_t + \beta_D \cdot \mathbb{I}(\textit{Distress})_{f,t-1} + \beta_R \cdot \textit{Relationship}_{b,f,t} + \beta_{RD} \cdot \textit{Relationship}_{b,f,t} * \mathbb{I}(\textit{Distress})_{f,t-1} + \gamma \cdot X_{b,f,t-1} + \varepsilon_{b,f,t}$$

in which $\textit{Loan Outcome}_{b,f,t}$ is either LOG(LOAN AMOUNT), ALL-IN DRAWN SPREAD, or ALL-IN UNDRAWN SPREAD, for a loan granted by lender b to borrower f currently outstanding at time t. $\alpha_f, \alpha_b, \alpha_t$ represent, respectively, borrower, lender, and year-quarter fixed effects. $\mathbb{I}(\textit{Distress})_{f,t-1}$ is a dummy equal to 1 if the borrower's EDF is greater than the 75th percentile of the distribution of EDFs for six or more months over $[t-4, t-1]$. $\textit{Relationship}_{b,f,t}$ is the fraction of loan events between lender b and borrower f over the total loan events of firm f occurred in the 5 years preceding the most recent loan event. $X_{b,f,t-1}$ is a vector of borrower, loan, and lender controls. Borrower controls include: credit rating dummies, size, book leverage, profitability, years since IPO, tangibility, liquidity, cash flows, market-to-book, dummy for issuance of any bond. Loan controls include dummies for loan types and loan purpose, the number of syndicate participants, and dummies for predominantly increasing and predominantly decreasing performance pricing grids. Lender controls include size and book equity. These controls are always included in the specifications. In parentheses t statistics are reported, obtained from clustering standard errors at the borrower level. ***, **, * indicate statistical significance at the 1%, 5% and 10%, respectively.

	LOG(LOAN AMOUNT)		ALL-IN DRAWN SPREAD		ALL-IN UNDRAWN SPREAD	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{I}(\textit{Distress})$	$.0779^{***}$	$.0779^{***}$	3.838	3.495	.6064	.4664
	(2.90)	(3.00)	(1.36)	(1.28)	(0.88)	(0.68)
Relationship	$.2284^{***}$	$.2117^{***}$	-21.39^{***}	-19.79^{***}	-2.681^{***}	-2.634^{***}
	(6.55)	(6.27)	(−7.29)	(−6.95)	(−3.68)	(−3.62)
$\textit{Relationship} * \mathbb{I}(\textit{Distress})$	$-.0981^{***}$	$-.095^{***}$	9.696^{**}	10.05^{**}	1.532	1.713^{*}
	(−2.71)	(−2.70)	(2.40)	(2.55)	(1.54)	(1.74)
Borrower FE & Year-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	–	Yes	–	Yes	–	Yes
Adj. R Sq.	.72	.725	.646	.655	.626	.629
Obs.	383,273	383,273	383,273	383,273	229,659	229,657
Net Effect $(\beta_R + \beta_{RD})$	$.13^{***}$	$.117^{***}$	-11.7^{**}	-9.74^{**}	−1.15	−.921
F-Stat	9.54	8.14	6.45	4.64	1.01	.668

Table A.5. The effect of relationship lending on other credit terms in distress

This table reports the estimates of the coefficients from the following regression over the sample of loan observations from the Dealscan main table, not including the loan modifications:

$$\begin{aligned} Loan\ Outcome_{b,f,t} = \ & \alpha_f + \alpha_b + \alpha_t + \beta_D \cdot \mathbb{I}(Distress)_{f,t-1} + \beta_R \cdot Relationship_{b,f,t} + \\ & \beta_{RD} \cdot Relationship_{b,f,t} * \mathbb{I}(Distress)_{f,t-1} + \gamma \cdot X_{b,f,t-1} + \varepsilon_{b,f,t} \end{aligned}$$

in which $Loan\ Outcome_{b,f,t}$ is either $\mathbb{I}$(COLLATERAL) or UPFRONT FEE for a loan granted by lender b to borrower f at time t. $\alpha_f, \alpha_b, \alpha_t$ represent, respectively, borrower, lender, and year-quarter fixed effects. $\mathbb{I}(Distress)_{f,t-1}$ is a dummy equal to 1 if the borrower's EDF is greater than the 75th percentile of the distribution of EDFs for six or more months over the rolling 12-month window preceding the given loan observation. $Relationship_{b,f,t}$ is the fraction of loan events between lender b and borrower f over the total loan events of firm f occurred in the 5 years preceding the given loan observation. $X_{b,f,t-1}$ is a vector of borrower, loan, and lender controls. Borrower controls include: credit rating dummies, size, book leverage, profitability, years since IPO, tangibility, liquidity, cash flows, market-to-book, dummy for issuance of any bond. Loan controls include dummies for loan types and loan purpose, the number of syndicate participants, and dummies for predominantly increasing and predominantly decreasing performance pricing grids. Lender controls include size and book equity. These controls are always included in the specifications. In parentheses t statistics are reported, obtained from clustering standard errors at the borrower level. ***, **, * indicate statistical significance at the 1%, 5% and 10%, respectively.

	$\mathbb{I}$(COLLATERAL)		UPFRONT FEE	
	(1)	(2)	(3)	(4)
$\mathbb{I}(Distress)$	.014	.0122	4.366	3.169
	(0.97)	(0.84)	(0.52)	(0.39)
Relationship	$-.0425^{***}$	$-.0365^{***}$	-9.102^{*}	-7.479
	(−3.68)	(−3.08)	(−1.92)	(−1.59)
$Relationship * \mathbb{I}(Distress)$	.0169	.0226	15.14	16.53
	(0.91)	(1.20)	(1.30)	(1.38)
Borrower FE & Year-Qtr FE	Yes	Yes	Yes	Yes
Lender FE	–	Yes	–	Yes
Adj. R Sq.	.678	.684	.509	.533
Obs.	14,764	14,757	3,025	3,018
Net Effect $(\beta_R + \beta_{RD})$	−.026	−.014	6.04	9.05
F-Stat	2.63	.725	.278	.599

Table A.6. Robustness: Alternative measures of relationship lending

This table reports the estimates of the coefficients from the following regression over the loan-quarter level sample, in which only loan facilities with a single lead arranger are included:

$$\textit{Loan Outcome}_{b,f,t} = \alpha_f + \alpha_b + \alpha_t + \beta_D \cdot \mathbb{I}(\textit{Distress})_{f,t-1} + \beta_R \cdot \textit{REL MES}_{b,f,t} + \beta_{RD} \cdot \textit{REL MES}_{b,f,t} * \mathbb{I}(\textit{Distress})_{f,t-1} + \gamma \cdot X_{b,f,t-1} + \varepsilon_{b,f,t}$$

in which $\textit{Loan Outcome}_{b,f,t}$ is either LOG(LOAN AMOUNT), ALL-IN DRAWN SPREAD, or ALL-IN UNDRAWN SPREAD, for a loan granted by lender b to borrower f currently outstanding at time t. $\alpha_f, \alpha_b, \alpha_t$ represent, respectively, borrower, lender, and year-quarter fixed effects. $\mathbb{I}(\textit{Distress})_{f,t-1}$ is a dummy equal to 1 if the borrower's EDF is greater than the 75th percentile of the distribution of EDFs for six or more months over $[t-4, t-1]$. In Panel A, *REL MES* is $\textit{Relationship (\$ Amt)}_{b,f,t}$, in Panel B *REL MES* is given by $\mathbb{I}(REL)$. $X_{b,f,t-1}$ is a vector of borrower, loan, and lender controls. Borrower controls include: credit rating dummies, size, book leverage, profitability, years since IPO, tangibility, liquidity, cash flows, market-to-book, dummy for issuance of any bond. Loan controls include dummies for loan types and loan purpose, the number of syndicate participants, and dummies for predominantly increasing and predominantly decreasing performance pricing grids. Lender controls include size and book equity. These controls are always included in the specifications. In parentheses t statistics are reported, obtained from clustering standard errors at the borrower level. ***, **, * indicate statistical significance at the 1%, 5% and 10%, respectively.

	LOG(LOAN AMOUNT)		ALL-IN DRAWN SPREAD		ALL-IN UNDRAWN SPREAD	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Relationship ($ Amt)	$.331^{***}$	$.311^{***}$	-26.58^{***}	-24.79^{***}	-2.832^{***}	-2.775^{***}
Relationship ($ Amt) $* \mathbb{I}(\textit{Distress})$	$-.1362^{***}$	$-.1293^{***}$	12.91^{***}	12.91^{***}	1.665^{*}	1.836^{*}
Adj. R Sq.	.722	.727	.648	.657	.626	.629
Net Effect $(\beta_R + \beta_{RD})$	$.195^{***}$	$.182^{***}$	-13.7^{***}	-11.9^{***}	-1.17	$-.938$
F-Stat	20.9	19.3	10.2	7.98	1.12	.747
Panel B						
$\mathbb{I}(REL)$	$.2233^{***}$	$.2073^{***}$	-17.94^{***}	-16.68^{***}	-2.622^{***}	-2.544^{***}
$\mathbb{I}(REL) * \mathbb{I}(\textit{Distress})$	$-.0636^{*}$	$-.0565$	10.25^{***}	10.38^{***}	1.505^{*}	1.674^{**}
Adj. R Sq.	.72	.725	.646	.655	.626	.629
Net Effect $(\beta_R + \beta_{RD})$	$.16^{***}$	$.151^{***}$	-7.69^{**}	-6.3^{*}	-1.12	$-.87$
F-Stat	15.4	14.8	3.91	2.76	1.84	1.14
Obs.	383,273	383,273	383,273	383,273	229,659	229,657
Borrower FE & Year-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	–	Yes	–	Yes	–	Yes

Table A.7. Robustness: Within-firm and within-bank analysis

This table reports the estimates of the coefficients from the following regression over the loan-quarter level sample, in which only loan facilities with a single lead arranger are included:

$$Loan\ Outcome_{b,f,t} = \alpha_{f,t} + \alpha_b/\alpha_{b,t} + \beta_R \cdot Relationship_{b,f,t} + \beta_{RD} \cdot Relationship_{b,f,t} * \mathbb{I}(Distress)_{f,t-1} + \gamma \cdot X_{b,f,t-1} + \varepsilon_{b,f,t}$$

in which *Loan Outcome*$_{b,f,t}$ is either LOG(LOAN AMOUNT), ALL-IN DRAWN SPREAD, or ALL-IN UNDRAWN SPREAD, for a loan granted by lender b to borrower f currently outstanding at time t. $\alpha_{f,t}$ represents fixed effects for each borrower/year-quarter pair. The specification can include either lender fixed effects, α_b, or fixed effects for each lender/year-quarter pair, $\alpha_{b,t}$. $\mathbb{I}(Distress)_{f,t-1}$ is a dummy equal to 1 if the borrower's EDF is greater than the 75th percentile of the distribution of EDFs for six or more months over $[t-4, t-1]$. *Relationship*$_{b,f,t}$ is the fraction of loan events between lender b and borrower f over the total loan events of firm f occurred in the 5 years preceding the most recent loan event. $X_{b,f,t-1}$ is a vector of borrower, loan, and lender controls. Borrower controls include: credit rating dummies, size, book leverage, profitability, years since IPO, tangibility, liquidity, cash flows, market-to-book, dummy for issuance of any bond. Loan controls include dummies for loan types and loan purpose, the number of syndicate participants, and dummies for predominantly increasing and predominantly decreasing performance pricing grids. Lender controls include size and book equity. These controls are always included in the specifications. In parentheses t statistics are reported, obtained from clustering standard errors at the borrower level. ***, **, * indicate statistical significance at the 1%, 5% and 10%, respectively.

	LOG(LOAN AMOUNT)		ALL-IN DRAWN SPREAD		ALL-IN UNDRAWN SPREAD	
	(1)	(2)	(3)	(4)	(5)	(6)
Relationship	.4018***	.3936***	−31.78***	−31.65***	−5.563***	−5.51***
	(7.23)	(7.05)	(−6.62)	(−6.57)	(−3.52)	(−3.49)
Relationship $* \mathbb{I}$(*Distress*)	−.2421***	−.252***	10.38	10.74	4.867*	5.073*
	(−3.13)	(−3.33)	(1.27)	(1.29)	(1.91)	(1.95)
Borrower × YearQtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	–	Yes	–	Yes	–
Lender × YearQtr FE	–	Yes	–	Yes	–	Yes
Adj. R Sq.	.72	.721	.733	.735	.772	.774
Obs.	347,334	347,044	347,334	347,044	186,076	185,550
Net Effect $(\beta_R + \beta_{RD})$	.16**	.142*	−21.4***	−20.9***	−.696	−.437
F-Stat	4.47	3.69	7.57	6.95	.084	.032

Table A.8. Robustness: Net effects of relationship lending using alternative definitions of distress

This table reports the estimates of the coefficients from the following regressions over the loan-quarter level sample, in which only loan facilities with a single lead arranger are included:

$$Loan\ Outcome_{b,f,t} = \alpha_f + \alpha_b + \alpha_t + \beta_D \cdot \mathbb{I}(Distress)_{f,t-1} + \beta_R \cdot Relationship_{b,f,t} + \beta_{RD} \cdot Relationship_{b,f,t} * \mathbb{I}(Distress)_{f,t-1} + \gamma \cdot X_{b,f,t-1} + \varepsilon_{b,f,t}$$

in which $Loan\ Outcome_{b,f,t}$ is either LOG(LOAN AMOUNT), ALL-IN DRAWN SPREAD, or ALL-IN UNDRAWN SPREAD, for a loan granted by lender b to borrower f currently outstanding at time t. $\alpha_f, \alpha_b, \alpha_t$ represent, respectively, borrower, lender, and year-quarter fixed effects. Each row reports the sum of the estimates for the coefficient β_R and β_{RD} obtained from using different definitions for $\mathbb{I}(Distress)_{f,t-1}$, described in the first column of the table. The first three rows define distress as described in Section 1.3.3, using three alternative thresholds: 70th, 80th, and 90th percentile. The fourth row define distress as a dummy variable that takes value 1 if the borrower's Altman Z-Score ≤ 1.8 and value 0 if it is ≥ 2.7, following the definition employed by Campello et al. (2018). $Relationship_{b,f,t}$ is the fraction of loan events between lender b and borrower f over the total loan events of firm f occurred in the 5 years preceding the most recent loan event. $X_{b,f,t-1}$ is a vector of borrower, loan, and lender controls. Borrower controls include: credit rating dummies, size, book leverage, profitability, years since IPO, tangibility, liquidity, cash flows, market-to-book, dummy for issuance of any bond. Loan controls include dummies for loan types and loan purpose, the number of syndicate participants, and dummies for predominantly increasing and predominantly decreasing performance pricing grids. Lender controls include size and book equity. These controls are always included in the specifications. In parentheses t statistics are reported, obtained from clustering standard errors at the borrower level. ***, **, * indicate statistical significance at the 1%, 5% and 10%, respectively.

	LOG(LOAN AMOUNT)		ALL-IN DRAWN SPREAD		ALL-IN UNDRAWN SPREAD	
Definition of *Distress*	(1)	(2)	(3)	(4)	(5)	(6)
EDF (threshold at 70th percentile)	$.131^{***}$	$.118^{***}$	-13.5^{***}	-11.5^{***}	-1.28	-1.05
F-Stat	9.87	8.54	9.9	7.5	1.53	1.07
EDF (threshold at 80th percentile)	$.136^{***}$	$.12^{***}$	-12.3^{**}	-10.1^{**}	-1.47	-1.21
F-Stat	8.86	7.41	6.23	4.34	1.37	.954
EDF (threshold at 90th percentile)	$.112^{**}$	$.101^{*}$	-12.5^{**}	-9.45	-1.77	-1.48
F-Stat	4.6	3.8	4.45	2.57	1.32	.946
Altman Z-Score (≤ 1.8)	$.203^{***}$	$.192^{***}$	-15.1^{***}	-13.8^{***}	-2.65^{**}	-2.54^{**}
F-Stat	19.8	19.7	14.9	13	5.55	5.22
Borrower FE & Year-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
	Yes	–	Yes	–	Yes	

Table A.9. Robustness: Including loans with multiple lead arrangers

This table reports the estimates of the coefficients from the following regression over the extended loan-quarter level sample, which includes also loan facilities with multiple lead arrangers:

$$Loan\ Outcome_{b,f,t} = \alpha_f + \alpha_b + \alpha_t + \beta_D \cdot \mathbb{I}(Distress)_{f,t-1} + \beta_R \cdot Relationship_{b,f,t} + \beta_{RD} \cdot Relationship_{b,f,t} * \mathbb{I}(Distress)_{f,t-1} + \gamma \cdot X_{b,f,t-1} + \varepsilon_{b,f,t}$$

in which $Loan\ Outcome_{b,f,t}$ is either LOG(LOAN AMOUNT), ALL-IN DRAWN SPREAD, or ALL-IN UNDRAWN SPREAD, for a loan granted by lender b to borrower f currently outstanding at time t. $\alpha_f, \alpha_b, \alpha_t$ represent, respectively, borrower, lender, and year-quarter fixed effects. $\mathbb{I}(Distress)_{f,t-1}$ is a dummy equal to 1 if the borrower's EDF is greater than the 75th percentile of the distribution of EDFs for six or more months over $[t-4, t-1]$. $Relationship_{b,f,t}$ is the fraction of loan events between lender b and borrower f over the total loan events of firm f occurred in the 5 years preceding the most recent loan event. $X_{b,f,t-1}$ is a vector of borrower, loan, and lender controls. Borrower controls include: credit rating dummies, size, book leverage, profitability, years since IPO, tangibility, liquidity, cash flows, market-to-book, dummy for issuance of any bond. Loan controls include dummies for loan types and loan purpose, the number of syndicate participants, and dummies for predominantly increasing and predominantly decreasing performance pricing grids. Lender controls include size and book equity. These controls are always included in the specifications. In parentheses t statistics are reported, obtained from clustering standard errors at the borrower level. ***, **, * indicate statistical significance at the 1%, 5% and 10%, respectively.

	LOG(LOAN AMOUNT)		ALL-IN DRAWN SPREAD		ALL-IN UNDRAWN SPREAD	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{I}(Distress)$	.0549	.0544	4.338	4.074	.7632	.6955
	(1.42)	(1.49)	(1.48)	(1.41)	(0.98)	(0.90)
Relationship	.2481***	.2184***	−24.36***	−23.18***	−2.983***	−2.924***
	(5.76)	(5.29)	(−7.99)	(−7.77)	(−3.63)	(−3.62)
Relationship $* \mathbb{I}(Distress)$	−.0775	−.0743	11.58***	11.9***	1.354	1.448
	(−1.45)	(−1.46)	(2.67)	(2.78)	(1.28)	(1.38)
Borrower FE & Year-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	–	Yes	–	Yes	–	Yes
Adj. R Sq.	.624	.632	.642	.649	.643	.645
Obs.	482,253	482,253	482,253	482,253	274,418	274,418
Net Effect $(\beta\_R + \beta\_RD)$	.171***	.144**	−12.8***	−11.3**	−1.63	−1.48
F-Stat	7.74	6.2	6.67	5.33	1.69	1.42

Table A.10. Robustness: Credit terms only in the presence of observable loan events (no pseudo credit register)

This table reports the estimates of the coefficients from the following regression over the sample of original loan observations, obtained from combining the main table of Dealscan and the loan modification table (*FACILITYAMENDMENT*):

$$Loan\ Outcome_{b,f,t} = \alpha_f + \alpha_b + \alpha_t + \beta_D \cdot \mathbb{I}(Distress)_{f,t-1} + \beta_R \cdot Relationship_{b,f,t} + \beta_{RD} \cdot Relationship_{b,f,t} * \mathbb{I}(Distress)_{f,t-1} + \gamma \cdot X_{b,f,t-1} + \varepsilon_{b,f,t}$$

in which $Loan\ Outcome_{b,f,t}$ is either LOG(LOAN AMOUNT), ALL-IN DRAWN SPREAD, or ALL-IN UNDRAWN SPREAD, for a new loan or loan modification between lender b and borrower f at time t. $\alpha_f, \alpha_b, \alpha_t$ represent, respectively, borrower, lender, and year-quarter fixed effects. $\mathbb{I}(Distress)_{f,t-1}$ is a dummy equal to 1 if the borrower's EDF is greater than the 75th percentile of the distribution of EDFs for six or more months over the rolling 12-month window preceding the given loan observation. $Relationship_{b,f,t}$ is the fraction of loan events between lender b and borrower f over the total loan events of firm f occurred in the 5 years preceding the given loan observation. $X_{b,f,t-1}$ is a vector of borrower, loan, and lender controls. Borrower controls include: credit rating dummies, size, book leverage, profitability, years since IPO, tangibility, liquidity, cash flows, market-to-book, dummy for issuance of any bond. Loan controls include dummies for loan types and loan purpose, the number of syndicate participants, and dummies for pred. increasing and pred. decreasing performance pricing grids. Lender controls include size and book equity. These controls are always included in the specifications. In parentheses t statistics are reported, obtained from clustering standard errors at the borrower level. ***, **, * indicate statistical significance at the 1%, 5% and 10%, respectively.

	LOG(LOAN AMOUNT)		ALL-IN DRAWN SPREAD		ALL-IN UNDRAWN SPREAD	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{I}(Distress)$	−.0101	−.014	31.23***	28.04***	5.197***	5.065***
	(−0.28)	(−0.39)	(6.58)	(5.94)	(5.26)	(5.10)
Relationship	.1398***	.128***	−16.29***	−13.74***	−.8367*	−.7986*
	(4.82)	(4.65)	(−6.47)	(−5.65)	(−1.77)	(−1.67)
$Relationship * \mathbb{I}(Distress)$	−.0291	−.0289	−5.13	−.6726	−2.718**	−2.526**
	(−0.65)	(−0.65)	(−0.84)	(−0.11)	(−2.27)	(−2.11)
Borrower FE & Year-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	–	Yes	–	Yes	–	Yes
Adj. R Sq.	.746	.751	.655	.666	.623	.626
Obs.	31,619	31,616	31,619	31,616	18,961	18,961
Net Effect $(\beta_R + \beta_{RD})$	.111**	.099**	−21.4***	−14.4**	−3.55***	−3.33***
F-Stat	6.54	5.13	12.9	5.81	8.25	7.28

Table A.11. Robustness: Stand-alone loan pricing terms

This table reports the estimates of the coefficients from the following regression over the loan-quarter level sample, in which only loan facilities with a single lead arranger are included:

$$\textit{Loan Outcome}_{b,f,t} = \alpha_f + \alpha_b + \alpha_t + \beta_D \cdot \mathbb{I}(\textit{Distress})_{f,t-1} + \beta_R \cdot \textit{Relationship}_{b,f,t} + \beta_{RD} \cdot \textit{Relationship}_{b,f,t} * \mathbb{I}(\textit{Distress})_{f,t-1} + \gamma \cdot X_{b,f,t-1} + \varepsilon_{b,f,t}$$

in which $\textit{Loan Outcome}_{b,f,t}$ is either LOAN SPREAD OVER LIBOR, COMMITMENT FEE, or ANNUAL FEE, for a loan granted by lender b to borrower f currently outstanding at time t. $\alpha_f, \alpha_b, \alpha_t$ represent, respectively, borrower, lender, and year-quarter fixed effects. $\mathbb{I}(\textit{Distress})_{f,t-1}$ is a dummy equal to 1 if the borrower's EDF is greater than the 75th percentile of the distribution of EDFs for six or more months over $[t-4, t-1]$. $\textit{Relationship}_{b,f,t}$ is the fraction of loan events between lender b and borrower f over the total loan events of firm f occurred in the 5 years preceding the most recent loan event. $X_{b,f,t-1}$ is a vector of borrower, loan, and lender controls. Borrower controls include: credit rating dummies, size, book leverage, profitability, years since IPO, tangibility, liquidity, cash flows, market-to-book, dummy for issuance of any bond. Loan controls include dummies for loan types and loan purpose, the number of syndicate participants, and dummies for predominantly increasing and predominantly decreasing performance pricing grids. Lender controls include size and book equity. These controls are always included in the specifications. In parentheses t statistics are reported, obtained from clustering standard errors at the borrower level. ***, **, * indicate statistical significance at the 1%, 5% and 10%, respectively.

	LOAN SPREAD		COMMITMENT FEE		ANNUAL FEE	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{I}(\textit{Distress})$	2.424	2.152	.532	.3166	.181	.2004
	(0.84)	(0.77)	(0.85)	(0.51)	(1.03)	(1.15)
Relationship	-23.08^{***}	-21.4^{***}	-2.849^{***}	-2.774^{***}	$.6646^{***}$	$.6484^{***}$
	(−7.82)	(−7.48)	(−4.15)	(−4.08)	(3.08)	(2.97)
$\textit{Relationship} * \mathbb{I}(\textit{Distress})$	9.897^{**}	10.2^{**}	.8693	1.142	−.0711	−.1016
	(2.40)	(2.53)	(0.95)	(1.28)	(−0.29)	(−0.42)
Borrower FE & Year-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	–	Yes	–	Yes	–	Yes
Adj. R Sq.	.661	.67	.719	.723	.454	.457
Obs.	375,241	375,240	229,125	229,123	382,975	382,975
Net Effect $(\beta_R + \beta_{RD})$	-13.2^{***}	-11.2^{**}	-1.98^{*}	−1.63	$.593^{**}$	$.547^{**}$
F-Stat	7.73	5.76	3.54	2.49	5	4.16

Table A.12. The effect of relationship lending in distress: The role of borrowers' outside options I

This table reports the estimates of the coefficients from the following regression over the baseline loan-quarter level sample, split by borrowers that issued a public bond before a given loan and borrowers that did not:

$$\textit{Loan Outcome}_{b,f,t} = \alpha_f + \alpha_b + \alpha_t + \beta_D \cdot \mathbb{I}(\textit{Distress})_{f,t-1} + \beta_R \cdot \textit{Relationship}_{b,f,t} + \beta_{RD} \cdot \textit{Relationship}_{b,f,t} * \mathbb{I}(\textit{Distress})_{f,t-1} + \gamma \cdot X_{b,f,t-1} + \varepsilon_{b,f,t}$$

in which $\textit{Loan Outcome}_{b,f,t}$ is either LOG(LOAN AMOUNT), ALL-IN DRAWN SPREAD, or ALL-IN UNDRAWN SPREAD, for a loan granted by lender b to borrower f currently outstanding at time t. $\alpha_f, \alpha_b, \alpha_t$ represent, respectively, borrower, lender, and year-quarter fixed effects. $\mathbb{I}(\textit{Distress})_{f,t-1}$ is a dummy equal to 1 if the borrower's EDF is greater than the 75th percentile of the distribution of EDFs for six or more months over $[t-4, t-1]$. $\textit{Relationship}_{b,f,t}$ is the fraction of loan events between lender b and borrower f over the total loan events of firm f occurred in the 5 years preceding the most recent loan event. $X_{b,f,t-1}$ is a vector of borrower, loan, and lender controls. Borrower controls include: credit rating dummies, size, book leverage, profitability, years since IPO, tangibility, liquidity, cash flows, market-to-book, dummy for issuance of any bond. Loan controls include dummies for loan types and loan purpose, the number of syndicate participants, and dummies for predominantly increasing and predominantly decreasing performance pricing grids. Lender controls include size and book equity. These controls are always included in the specifications. In parentheses t statistics are reported, obtained from clustering standard errors at the borrower level. ***, **, * indicate statistical significance at the 1%, 5% and 10%, respectively.

	LOG(LOAN AMOUNT)		ALL-IN DRAWN SPREAD		ALL-IN UNDRAWN SPREAD	
	Bond Market	No Bond Market	Bond Market	No Bond Market	Bond Market	No Bond Market
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{I}(\textit{Distress})$	$.0897^{**}$	$.0441^{*}$	$-.4157$	6.192^{**}	$-.0848$	$.6599$
	(2.16)	(1.69)	(−0.095)	(2.09)	(−0.078)	(0.96)
Relationship	$.304^{***}$	$.0954^{**}$	-25.16^{***}	-13.53^{***}	-3.834^{***}	-1.645^{**}
	(6.36)	(2.19)	(−6.37)	(−3.44)	(−4.07)	(−2.00)
$\textit{Relationship} * \mathbb{I}(\textit{Distress})$	$-.1295^{**}$	$-.0477$	16.83^{***}	2.298	2.651^{*}	$.6534$
	(−2.33)	(−1.24)	(2.70)	(0.54)	(1.77)	(0.65)
Borrower FE & Year-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R Sq.	.633	.759	.644	.702	.645	.666
Obs.	206,678	176,550	206,678	176,550	129,663	99,943
Net Effect $(\beta_R + \beta_{RD})$	$.175^{***}$	.048	−8.33	-11.2^{**}	−1.18	−.991
F-Stat	6.87	1.04	1.52	3.99	.472	.651

Table A.13. The effect of relationship lending in distress: The role of borrowers' outside options II

This table reports the estimates of the coefficients from the following regression over the baseline loan-quarter level sample, split by borrowers that recently issues a public bond (in the 3 years preceding last loan event) and those that did not:

$$Loan\ Outcome_{b,f,t} = \alpha_f + \alpha_b + \alpha_t + \beta_D \cdot \mathbb{I}(Distress)_{f,t-1} + \beta_R \cdot Relationship_{b,f,t} + \beta_{RD} \cdot Relationship_{b,f,t} * \mathbb{I}(Distress)_{f,t-1} + \gamma \cdot X_{b,f,t-1} + \varepsilon_{b,f,t}$$

in which $Loan\ Outcome_{b,f,t}$ is either LOG(LOAN AMOUNT), ALL-IN DRAWN SPREAD, or ALL-IN UNDRAWN SPREAD, for a loan granted by lender b to borrower f currently outstanding at time t. $\alpha_f, \alpha_b, \alpha_t$ represent, respectively, borrower, lender, and year-quarter fixed effects. $\mathbb{I}(Distress)_{f,t-1}$ is a dummy equal to 1 if the borrower's EDF is greater than the 75th percentile of the distribution of EDFs for six or more months over $[t-4, t-1]$. $Relationship_{b,f,t}$ is the fraction of loan events between lender b and borrower f over the total loan events of firm f occurred in the 5 years preceding the most recent loan event. $X_{b,f,t-1}$ is a vector of borrower, loan, and lender controls. Borrower controls include: credit rating dummies, size, book leverage, profitability, years since IPO, tangibility, liquidity, cash flows, market-to-book, dummy for issuance of any bond. Loan controls include dummies for loan types and loan purpose, the number of syndicate participants, and dummies for predominantly increasing and predominantly decreasing performance pricing grids. Lender controls include size and book equity. These controls are always included in the specifications. In parentheses t statistics are reported, obtained from clustering standard errors at the borrower level. ***, **, * indicate statistical significance at the 1%, 5% and 10%, respectively.

	LOG(LOAN AMOUNT)		ALL-IN DRAWN SPREAD		ALL-IN UNDRAWN SPREAD	
	Recent Bond	No Recent Bond	Recent Bond	No Recent Bond	Recent Bond	No Recent Bond
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{I}(Distress)$	.0744	.0653**	−4.525	12.02***	−1.407	1.987***
	(1.54)	(2.54)	(−1.03)	(3.63)	(−1.20)	(2.93)
Relationship	.3435***	.1121***	−25.56***	−16.38***	−3.76***	−1.825***
	(6.30)	(3.05)	(−5.63)	(−4.77)	(−2.99)	(−2.62)
$Relationship * \mathbb{I}(Distress)$	−.1062*	−.0816**	19.71***	−.7155	4.684***	−.7075
	(−1.69)	(−2.29)	(3.08)	(−0.16)	(2.66)	(−0.76)
Borrower FE & Year-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R Sq.	.648	.756	.659	.685	.651	.662
Obs.	166,245	216,959	166,245	216,959	104,022	125,548
Net Effect $(\beta_R + \beta_{RD})$	.237***	.03	−5.85	−17.1***	.924	−2.53**
F-Stat	9.51	.519	.722	9.53	.211	5

Table A.14. Variable definitions

Variable Name	Definition	Data Source
Specialization	Rolling 12-qtr sum of specialization dummy, as defined in Equation (2.4)	Dealscan
Specialization (nY)	Rolling $4n$-qtr sum of specialization dummy, as defined in Equation (2.4)	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)	$\text{Ln}\left(1+\frac{\text{rolling 4-qtr sum of }\texttt{oibdq}}{\text{rolling 4-qtr sum of }\texttt{xintq}}\right)$	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 2.2.3	Dealscan
Rel. Intensity (Amt)	Described in Section 2.2.3	Dealscan
Rel. Intensity (Num)	Described in Section 2.2.3	Dealscan
Rel. Length	Described in Section 2.2.3	Dealscan
Market Share	Described in Section 2.2.3	Dealscan
Same State	Described in Section 2.2.3	Compustat/SEC
Defaults	N. outstanding loans to firms with cred. rat. changed to "D"/"SD" over prev. qtr	Dealscan/Capital IQ

Table A.15. Descriptive statistics

This table reports the descriptive statistics for the full matched Dealscan-Compustat sample obtained after applying the selection criteria described in Section 2.2.1, 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 A.14. 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 A.16. Univariate evidence on loan contracts and bank-firm selection

This table reports the results of univariate t-tests, 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 variable X listed in the table, H_0 is that $E[X(\textit{Specialized}) - X(\textit{Non-Specialized})] = 0$.

	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 A.17. The effect of bank specialization on covenant strictness and loan spread

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

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

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 A.14. 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 A.18. Bank specialization and loan terms, accounting for bank-firm 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 A.14. 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 A.19. 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:

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

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 A.14. 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 A.20. 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:

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

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 A.14. 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 A.21. 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 A.14. 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 A.22. 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:

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

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 A.14. 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 A.23. 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 A.14. 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 A.24. 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 A.14. 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 A.25. 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:

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

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 A.14. 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

A.2. FIGURES

Figure A.1. An example of state-contingent loan pricing

The figure represents the difference between the level of the All-In Drawn Spread (AISD) at origination (blue line) and the AISD implied by the performance pricing grid (red line) over the lifetime of a revolver credit facility that was issued on November 8, 1995 to Burlington Industries (Dealscan *facilityid* 35978). The performance pricing grid is based on the S&P Lon Term Issuer Credit Rating. The shaded areas represent quarters of financial distress according to the measure described in Section 1.3.3.

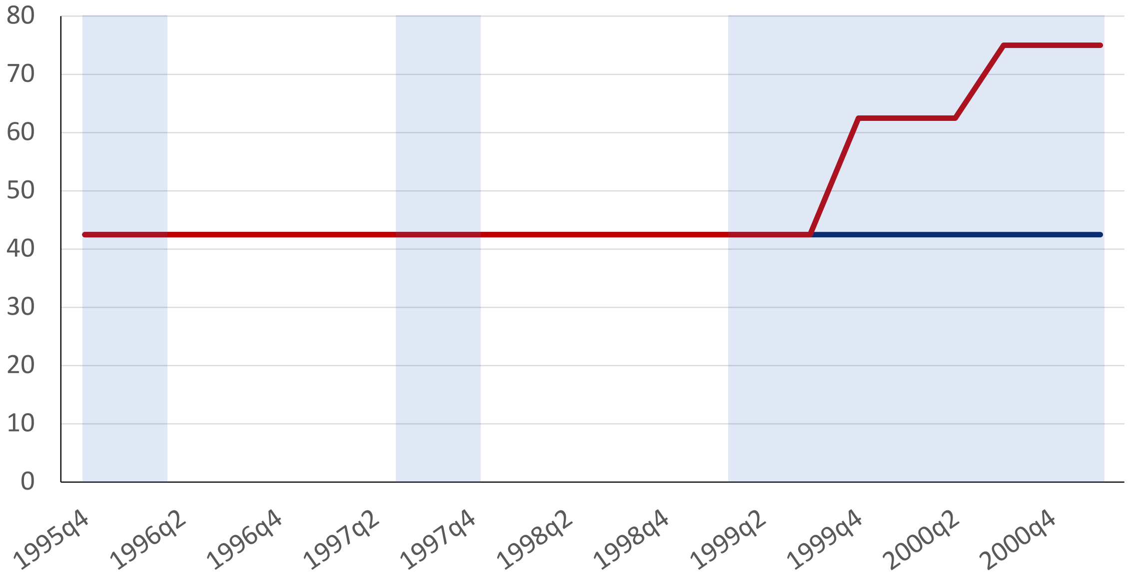


Figure A.2. Simple examples to understand bank specialization

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.

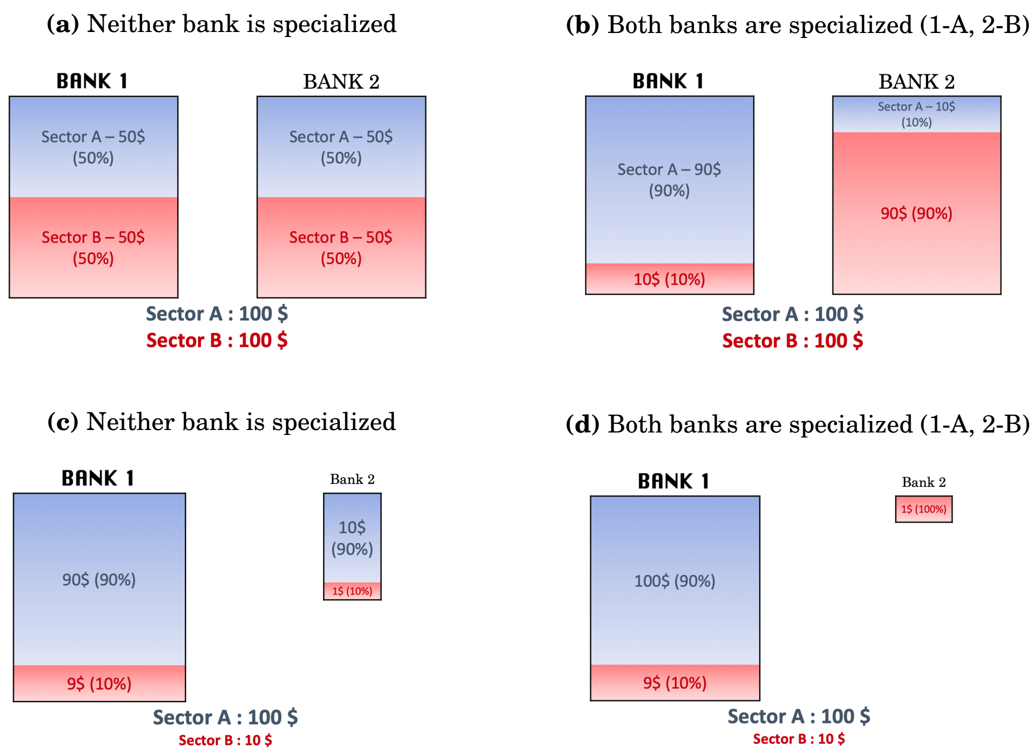


Figure A.3. Comparison between portfolio concentration of the average bank and the "market"

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.

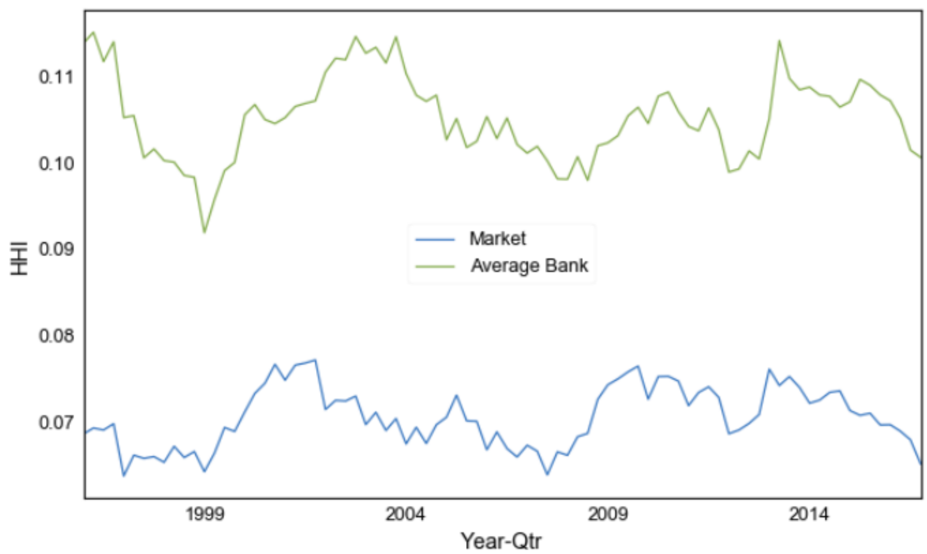


Figure A.4. Specialization is common across industries and time

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.

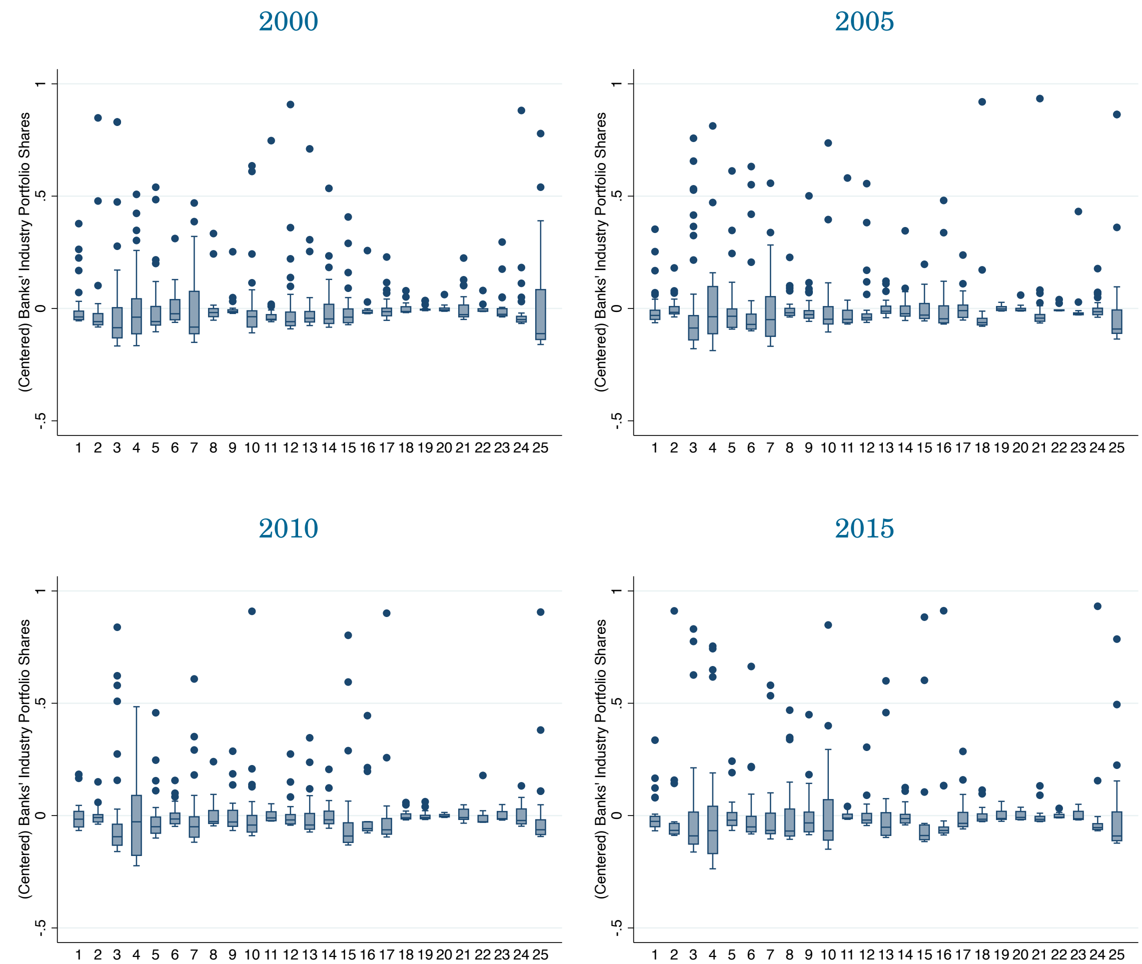
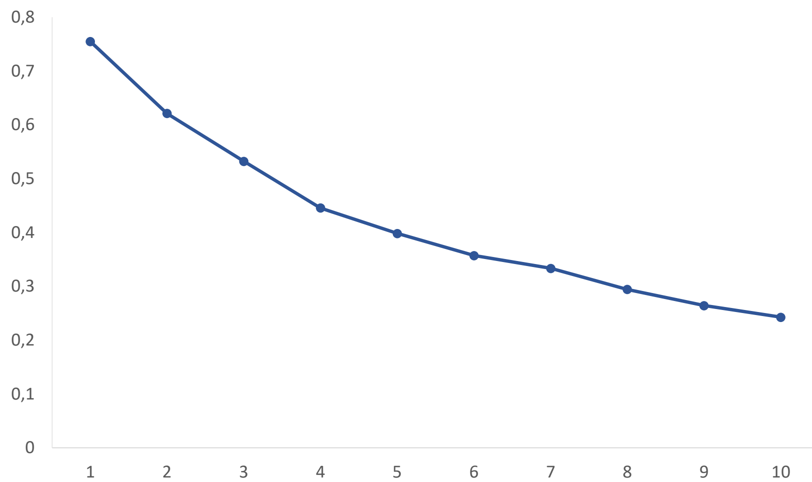


Figure A.5. Specialization is persistent over time

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.



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