Bank Specialization and Credit Relationships in Small-Business Lending*

Yannis Cabossioras[†] Joris Tielens[‡]

November 14, 2024

Click for latest version

Abstract

We study the dynamics of credit relationships between small businesses and specialized banks and analyze the real effects of specialization on this important yet understudied segment of the credit market. Using micro-level data on the universe of corporate credit in Belgium, we show that banks leverage their industry specialization to build and retain relationships with small businesses. In the relationship-building phase, banks charge lower rates in their industries of specialization. In the relationship-retaining phase, lenders subsequently raise rates faster in specialized industries, until they charge similar rates regardless of their level of specialization. Specialized banks internalize the intertemporal value of credit relationships, combining both industry knowledge and market power to extract value from their relationships. Small businesses benefit from bank specialization in the long run through higher growth in investment, profitability, productivity, and equity value. The real effects of bank specialization inform policies that could inhibit banks incentives to specialize, such as open banking policies.

JEL codes: D22, G21, L1, L25, O52

Keywords: Bank specialization, Small-business lending, Credit relationships, Industry expertise, Market power

---

* Cabossioras is deeply grateful to his advisors Anthony Saunders, Simone Lenzu, and Cecilia Parlatore for their invaluable guidance and dedicated support. We thank Joshua Coven, Holger Mueller, Alex Osberghaus, Stefano Pastore, Helena Pedrotti, Alexi Savov, Philipp Schnabl, Pascal Ungersboeck, Courtney Wiegand, as well as seminar participants at the ECB's DGR internal seminar, the 2024 Community Banking Research Conference, NYU Stern's internal finance seminar, and the Inter-Finance PhD Seminar for their insightful comments and suggestions. Cabossioras gratefully acknowledges support from the Fubon Center for Technology, Business and Innovation and the National Bank of Belgium. The views expressed in this paper are those of the authors and do not necessarily reflect the views of the National Bank of Belgium or the Eurosystem. All errors are our own.

[†]New York University – Stern School of Business, email: yannis.cabossioras@stern.nyu.edu.

[‡]National Bank of Belgium, email: joris.tielens@nbb.be.

While small businesses represent 99% of firms, employ half of the workforce, and account for a third of sales in the US and the European Union, their opacity limits access to external funding opportunities (Stiglitz and Weiss, 1981; Fazzari et al., 1988; Gertler and Gilchrist, 1994).[1] This constraint compels small businesses to establish long-term credit relationships to mitigate these information asymmetries (Petersen and Rajan, 1994; Berger and Udell, 1995).

Lenders specialized in financing specific segments of the credit market are better positioned to develop strong relationships. These lenders can screen and monitor borrowers more efficiently and offer more favorable loan terms (Berger, Minnis and Sutherland, 2017; Blickle, Parlatore and Saunders, 2024). Specialized lenders also provide products and services tailored to the firm's industry such as custom underwriting or insights on supply chain management, macroeconomic trends, and regulatory requirements (Paravisini, Rappoport and Schnabl, 2023). Therefore, specialized lenders are particularly well-suited to provide credit to small businesses.

However, consistent with the holdup problem recognized by Sharpe (1990), Rajan (1992), and Santos and Winton (2008), specialized lenders may use these advantages to extract surplus from long-standing borrowers facing high relationship-switching costs. Given these conflicting forces, do small businesses benefit from relationships with specialized lenders? This question is crucial to inform policies that could inhibit banks' incentives to specialize, such as open banking policies currently being implemented in the US and the European Union.

In this paper, we document the differential lending dynamics of banks across their industries of specialization and study the implications on small businesses' real outcomes using micro-level data on the universe of corporate credit in Belgium. First, we show that specialized banks adjust their lending behavior to draw and retain borrowers. Specifically, during the initial relationship-building phase, banks offer lower rates to borrowers in their industries of specialization. In the relationship-retaining phase, lenders subsequently raise rates faster in specialized industries, until they charge similar rates regardless of their level of specialization. Second, we interpret this building-retaining behavior as evidence that banks internalize the intertemporal value of credit relationships, combining both industry knowledge and market power to extract value from these specialized relationships. Third, we find that on net specialized lending is associated with better outcomes for small businesses in the long run.

[1] Sources: US Small Business Administration (2023) and Eurostat (2024). In the European Union, small businesses are defined as enterprises employing up to 49 persons, while the US categorizes them as firms with up to 500 employees, although among these 98% have less than 19 employees.

We use regulatory data on the universe of corporate credit in Belgium from the National Bank of Belgium (NBB). As part of AnaCredit—the Eurozone's credit registry—eligible institutions report contract-level information on every credit facility extended to firms operating in Belgium. Data on small-business lending is notoriously scarce, however credit institutions in Belgium are not subject to any minimum reporting thresholds, allowing us to capture the entire distribution which is heavily skewed toward smaller firms. Additionally, most contracts contain firm-level default probabilities internally assessed under the Basel II Internal Ratings-Based (IRB) approach, essential to dealing with the opacity of small businesses. On the credit supply side, the Belgian banking sector is highly concentrated, with four banks capturing over 90% of total lending. Therefore, the banking landscape in Belgium provides a unique setting to study the interplay between lending specialization, bank concentration, and small businesses.

We augment the credit registry data with balance sheets and income statements on every VAT-liable firm in Belgium collected from the central balance sheet office, firm VAT declarations, and social security declarations. These statements provide a unique insight into small businesses' financials usually available only for larger public firms.

We define specialization as the deviation from the bank's portfolio weight in a given industry from the weight of that industry in overall corporate credit following Blickle et al. (2024).[2] Intuitively, a bank specializes in an industry if a sector is overweighted in its stock of outstanding credit relative to a diversified portfolio where weights are proportional to sector size.

The effect of bank specialization on interest rates is ex-ante unclear. On one hand, specialized banks have better information acquisition technologies which translate into lower screening and monitoring costs (Blickle et al., 2024). On the other hand, banks with industry experience can cater to their borrower needs through custom underwritten contracts and advisory services. These differentiated services potentially give specialized banks market power over their borrowers, enabling them to charge higher rates (Degryse and Ongena, 2005; Crawford, Pavanini and Schivardi, 2018; Whited, Wu and Xiao, 2021). In this paper, we consider both channels by comparing lenders' pricing decisions across their industries of specialization over the entire length of the relationship.

Additionally, from an identification perspective, the pricing decisions of specialized banks throughout their credit relationship might be confounded by two types of selection. At the beginning of the relationship, the lower rates charged by banks in their industries

[2] Other similar measures of specialization based on a bank's stock of outstanding credit have been proposed in the recent literature, see e.g., Duquerroy et al. (2022); Giometti and Pietrosanti (2022); Paravisini, Rappoport and Schnabl (2023); Blickle et al. (2024); Degryse et al. (2024).

of specialization could be result of better firms matching with specialized banks. The subsequent rise in interest rates over the course of the relationship could be due to selected attrition.

We address selection in three ways. First, we purge unobserved factors responsible for selection by saturating our specification with relationship fixed effects. Second, rate disparities across industries might reflect heterogeneity in borrower riskiness. We leverage the granularity of lender-assessed ex-ante default probabilities to credibly purge interest rates from risk-based considerations. Third, due to the availability of balance sheets for even the smallest firms, we explicitly control for an exhaustive set of firm characteristics that may affect credit demand.

In Section 3, we establish that banks' dynamic pricing strategies differ across their industries of specialization. In the first three years of relationships in their preferred industries, banks charge interest rates 30 bp lower compared to industries they are diversified in. Banks subsequently close this gap by raising their rates faster in their industries of specialization. After 12 years, they charge similar rates across industries regardless of their degree of specialization. We identify this result by estimating a tight specification. First, we only keep credit contracts at the time of origination or renegotiation to capture active lending decisions. Second, bank-time fixed effects remove bank-level factors confounded with our measure of specialization. Third, we control for observable heterogeneity with a rich set of covariates at the contract, relationship, and borrower level. Fourth, we use firm-level default probabilities assessed by lenders to purge rates from risk premia. Finally, we account for selected matching and attrition by including relationship fixed effects.[3]

We subsequently draw implications from this pricing behavior about the sources of lender specialization. The trajectory of interest rates suggests that specialized lenders develop market power over their borrowers over the course of their relationship. In the relationship-building phase, specialized banks compete with other lenders and offer lower rates to attract borrowers. Once their relationship is established, small businesses are reluctant to switch away from the benefits specialized lenders provide through industry-tailored products and expertise (Paravisini, Rappoport and Schnabl, 2023). This local monopoly power allows lenders to increase their rates faster in their preferred industries. Despite this increase, lenders charge lower rates in their industries of specialization throughout their relationships. The absence of rent extraction of specialized banks in the later stage of relationships as theorized by Petersen and Rajan (1995) is consistent

[3] In our most stringent specifications, firm-time fixed effects absorb the unobserved firm default risk and credit demand. The results are identified off variation in interest rates charged to the same firm by several lenders with varying degrees of specialization.

with lenders having better industry knowledge and lower screening and monitoring costs in their preferred industries (Berger, Minnis and Sutherland, 2017; Blickle, Parlatore and Saunders, 2024; Bonfim et al., 2024).

Within lenders' preferred industries, we find that riskier firms are more exposed to the building-retaining behavior of specialized banks. This result is consistent with riskier small businesses depending more on specialized relationships due to difficulty obtaining financing from non-specialized lenders, or placing a higher value on specialized expertise. The same result holds for other borrowers relying heavily on their credit relationships, such as firms with fewer lenders and larger loan amounts outstanding. We also find evidence of these rate dynamics on firm decisions both on the extensive and intensive margin. Firms that belong to a bank's industry of specialization obtain relatively larger contracts and are less likely to end their relationship early on. As interest rates increase, contract sizes progressively decrease and firms are relatively more likely to separate from specialized lenders.

In Section 4, we show that specialized lending is associated with better firm outcomes in the long run. Firms are more likely to borrow from specialized lenders and have longer relationships, especially risky firms. These sorting patterns cannot be fully explained by borrowers facing search frictions or being rejected by non-specialized lenders, otherwise specialized banks would not offer lower rates in the relationship-building phase. Over the course of their relationship, small businesses borrowing from specialized lenders have higher growth in sales, return-on-assets, equity value, and capital expenditure. We alleviate concerns about selected matching and attrition by including relationship fixed effects. Overall, these results shed some light on the nature of lender market power, as specialized lenders and their borrowers seem to play a positive-sum game.

In light of the previous results, the impact of bank specialization on the financing of small businesses has a clear implication for policy. In industries where banks specialize, more credit is directed toward riskier and younger firms which are often credit-constrained. By improving firms' access to credit, specialized banks foster firm entry and competition in product markets (Berger and Udell, 1998; Black and Strahan, 2002; Cetorelli and Strahan, 2006). Thus, policies hindering banks' incentives to specialize could raise barriers to entry.

In particular, recent open banking policies increase information sharing across financial institutions to foster competition. For instance, the European Payment Services Directive 2 (PSD2), enforced since 2018, allows third-party providers to access customer financial data through standardized APIs. In the US, the Consumer Financial Protection Bureau (CFPB) recently finalized a rule to allow consumers to transfer their personal financial data across institutions.[4] By reducing banks' informational advantages over their borrowers, these open banking policies could weaken lenders' incentives to develop expertise ex-ante through specialization.

We draw from and contribute to three strands of literature. First, this paper bridges the gap between the literature on relationship lending and the literature on bank specialization. Relationship lenders are able to mitigate information asymmetries by learning about opaque borrowers through repeated interactions (Diamond, 1984; Boot and Thakor, 1994).[5] These relationships alleviate credit rationing (Stiglitz and Weiss, 1981; Fazzari et al., 1988; Gertler and Gilchrist, 1994), benefiting small businesses through larger credit amounts (Petersen and Rajan, 1994), lower interest rates, lower pledged collateral (Berger and Udell, 1995; Bharath et al., 2011), better protection against adverse financial shocks, and can be used as a signaling device for alternative funding opportunities (James, 1987; Lummer and McConnell, 1989).[6] The literature on bank specialization establishes that lenders develop market-specific knowledge by specializing into certain segments of the credit market and points out the benefits of bank specialization.[7,8] This paper merges these two literatures by decomposing the lending behavior of specialized banks throughout their relationships with small businesses. Our results highlight the complementarity between specialization and relationships since banks use their industry expertise to attract new borrowers by offering advantageous loans terms early on.

Second, our work advances the literature on the long-term effects of information and market power on relationships. The holdup problem describes how relationship lenders can extract surplus from their borrowers. This effect gets stronger as lender competition decreases and as the informational gap with outside lenders widens (Petersen and Rajan,

[4] The rule was announced on October 22, 2024 and carries out the personal financial data rights established by the Consumer Financial Protection Act of 2010 (CFPA).

[5] Specifically, relationship lenders collect soft information (Stein, 2002; Berger et al., 2005), rely on the judgment of loan officers (Uchida, Udell and Yamori, 2012; Papoutsi, 2024), and develop geographical expertise (Degryse and Ongena, 2005; Mian, 2006; Agarwal and Hauswald, 2010; Chen and Song, 2013).

[6] See, e.g., Cotugno, Monferrà and Sampagnaro (2013); Deyoung et al. (2015); Sette and Gobbi (2015); Bolton et al. (2016); Karolyi (2018); Schwert (2018); Banerjee, Gambacorta and Sette (2021) for evidence that lenders protect their relationships during economic downturns.

[7] Lenders are known to specialize in specific industries (Blickle, Parlatore and Saunders, 2024), location (Berger, Minnis and Sutherland, 2017; Duquerroy et al., 2022), exports markets (Paravisini, Rappoport and Schnabl, 2023), types of debt (Carey, Post and Sharpe, 1998; Granja, Matvos and Seru, 2017; Blickle, 2022), types of collateral (Gopal and Schnabl, 2022), and firm types (Bonfim et al., 2024).

[8] Specialized lenders give larger amounts, lower rates and less restrictive financial covenants (Berger, Minnis and Sutherland, 2017; Giometti and Pietrosanti, 2022; Blickle, Parlatore and Saunders, 2024), offer expertise and tailored products (Paravisini, Rappoport and Schnabl, 2023), and protect their borrowers against adverse financial shocks (De Haas and Van Horen, 2012; Giannetti and Saidi, 2019; De Jonghe, Dewachter and Ongena, 2020; Jiang and Li, 2022).

1995; Boot and Thakor, 2000).[9] Specialized banks also obtain informational advantages over their competitors by lending to specific segments of the credit market.[10] We contribute by showing that specialization exacerbates the holdup problem given the steeper increase in rates over time, although firms still benefit from specialized relationships overall. We are the first to show direct evidence of market power by specialized lenders on prices.[11]

Third, this paper adds to the literature on the benefits of bank specialization. While some theoretical work argue in favor of lender diversification to limit information asymmetries (Diamond, 1984; Boyd and Prescott, 1986), lenders generally benefit from specialization.[12] On the firm side, Degryse et al. (2024) find mixed evidence of the effect of specialization on firm innovation. We contribute by showing that small businesses who borrow from specialized lenders have better real outcomes over the course of their relationships. We also contribute to the literature on the real effects of financing frictions on small businesses' real activity. Financing frictions are an important barrier to entry for new firms, and credit constraints restrict the growth of small businesses.[13] By offering advantageous credit conditions to new and relationship-dependent borrowers, we highlight the role of specialized banks in alleviating these credit constraints, particularly for young and risky firms.

The remainder of the paper proceeds as follows. Section 1 develops the conceptual framework and testable predictions motivating our empirical analysis. Section 2 presents the data on the Belgian corporate credit market and exposes facts about credit relationships and bank specialization in Belgium. Section 3 contains our main results on the dynamic behavior of specialized banks throughout their credit relationships. Section 4 studies the effect of specialized relationships on firm real outcomes. Section 5 concludes.

[9] Models of the holdup problem include Sharpe (1990), Rajan (1992), and von Thadden (2004) while Santos and Winton (2008); Ioannidou and Ongena (2010); and Kosekova et al. (2023) show that better-informed lenders extract surplus from their borrowers.

[10] See, e.g., Berger, Minnis and Sutherland (2017); Paravisini, Rappoport and Schnabl (2023); Blickle, Parlatore and Saunders (2024); Blickle et al. (2024); Bonfim et al. (2024).

[11] Paravisini, Rappoport and Schnabl (2023) find some indirect evidence of market power by showing that borrowers are more likely to choose a lender specialized in their target export market, and arguing that they do so because of the differentiated products and services specialized lenders offer.

[12] See, e.g., Diamond (1984); Boyd and Prescott (1986); Winton (1999); Acharya, Hasan and Saunders (2006); Jahn, Memmel and Pfingsten (2016); Gelman, Goldstein and MacKinlay (2023).

[13] See, e.g., Black and Strahan (2002); Beck, Demirgüc-Kunt and Maksimovic (2005); Cetorelli and Strahan (2006); Banerjee and Duflo (2014).

1 Hypothesis Development

We motivate the empirical analysis by providing a conceptual framework to understand the rate-setting decisions of specialized banks in the context of their relationships with small businesses. Throughout this section, we hold borrower riskiness fixed.

Bank specialization and relationship lenders arise from the same common root which is the tendency of lenders to collect information to mitigate information asymmetries. While specialized banks collect information by lending to specific segments of the credit market, relationship lenders learn about their borrowers through repeated interactions. The complementarity nature of these information acquisition technologies suggests that they might interact with each other and motivates why they should be considered jointly.

We build upon theories of the holdup problem from Sharpe (1990) and Rajan (1992) studying the equilibrium effects of heterogeneous lender information on financing conditions. Banks establish relationships to learn about opaque borrowers and use the informational gap with uninformed lenders to extract surplus from their borrowers. In a Bertrand-Nash competition setting, the holdup problem means that as relationship-switching costs make a borrower's credit demand less elastic, lenders charge a higher markup throughout their relationship.[14]

Banks build knowledge by specializing in their portfolio toward specific segments of the credit market (Berger, Minnis and Sutherland, 2017; Blickle, Parlatore and Saunders, 2024). In the case of industry specialization, banks have lower screening and monitoring costs in their preferred industries. They also offer products tailored to the needs of their borrowers—such as custom underwriting or bundling deposit accounts with credit contracts—and provide industry expertise to financially unsophisticated borrowers on supply chain management, macroeconomic trends, and regulatory requirements (Paravisini, Rappoport and Schnabl, 2023). Therefore, lenders derive larger value out of their relationships in their industries of specialization.

The ability of specialized banks to build and retain relationships affects their rate-setting decisions. Before a match occurs, lenders have to compete for prospective borrowers. They internalize the intertemporal value of relationships and attract borrowers by initially offering lower rates.[15] Lenders understand that the short term revenue loss from offering teaser rates early on is offset by the higher expected future revenues from

[14] While relationship lenders raise their markups over time, interest rates might not increase if lending costs decrease over the relationship, e.g., due to lower risk premia.

[15] We assume that borrowers do not fully internalize the intertemporal value of specialized relationships, a reasonable assumption in the context of small-business lending since these firms are likely to be financially unsophisticated.

repeated interactions once the relationship is established. In particular, this relationship-building behavior is stronger for specialized banks which derive more value out of their relationships.

Prediction 1 Specialized lenders offer lower rates early on in their relationships.

Once a relationship is established, switching costs effectively make the continuation value less sensitive to changes in the interest rate. Lenders take advantage of this inelastic demand to holdup their borrowers and raise their markups. Borrowers in specialized relationships face stronger holdup since they derive larger benefits from the products and expertise offered by specialized lenders.

Prediction 2 Specialized lenders increase their rates faster over the course of their relationships.

Firms borrowing from specialized banks respond to the invest-harvest behavior. In the invest phase, these borrowers take advantage of attractive rates and are more likely to stay in their specialized relationships. In the harvest phase, borrowers respond to stronger rate increases and are more likely to end their relationships.

Prediction 3 Firms should react to the invest-harvest behavior of specialized banks.

Petersen and Rajan (1995) study lending relationships in the context of credit market competition and find that lenders subsidize new relationships in noncompetitive markets to extract rents later on through stronger holdup. Banks exert market power in noncompetitive markets, just as banks exert market power in their area of specialization and intuitively both lead to similar invest-harvest behavior. However, while lenders eventually charge higher rates on less competitive markets to make up for early subsidies, specialized lenders need not charge higher rates than non-specialized lenders if their lending costs are lower. Thus, specialized lenders can still exert harvest behavior despite charging lower rates over the entire relationship.

Throughout this section, we have assumed that firm riskiness is fixed, but specialized banks might be able to screen for safer borrowers and reduce risk through better monitoring. These differences in borrower risk profiles could confound identification of the invest-harvest behavior. Thus, isolating lenders' pricing behavior in the context of specialization and relationships requires controlling for firm riskiness accurately.

d

2 Bank Specialization and Credit Relationships in Belgium

This section describes data on the Belgian corporate credit market used to test the invest-harvest behavior of specialized banks formulated in Section 1. We subsequently report a set of facts about bank specialization and relationship lending to establish that Belgium serves as an ideal laboratory to test these predictions.

2.1 Data

We use credit registry data from two main sources maintained by the National Bank of Belgium (NBB). First, the Belgian Extended Credit Risk Information System (BECRIS) contains contract-level information on the universe of corporate credit in Belgium from 2018 Q3 to 2023 Q4. It is the Belgian implementation of the analytical credit datasets (AnaCredit) initiated by the European Central Bank (ECB) to provide harmonized credit data collection guidelines across members of the Eurozone. Each contract records all counterparties involved (e.g., debtor, creditor, originator, servicer) as well as information about the type of instrument, protection, securitization, and performing status.[16]

Crucially, all Belgian credit institutions—including Belgian branches of foreign institutions and subsidiaries of foreign firms incorporated in Belgium—have to report their outstanding commitments to any firm regardless of their nationality, the type of instrument, or the amount committed. Smaller contracts often fall below the reporting thresholds set by regulators, so credit registries might not capture the full extent of credit granted to small businesses. As a comparison, the FR Y-14 credit registry data maintained by the US Federal Reserve focuses on medium and large firms and requires only bank commitments above $1 million to be reported. In BECRIS, 93% of contracts have outstanding amounts below this threshold and represent 40% of total lending and 45% of total employment. Thus, BECRIS offers a complete picture of the Belgian corporate credit market and, in particular, of small-business lending.

We gain a longer historical perspective by supplementing our analysis with data from the Belgian Corporate Credit Register (CCR), the predecessor of BECRIS, which runs from 2012 Q2 to 2021 Q4.[17] While interest payments are not recorded in the CCR, it contains total outstanding commitments between a credit institution and a firm. We use these data to extend our series of bank specialization defined in Section 2.3 below over a longer

[16] Loan applications and additional contract characteristics such as fees and covenants are not reported.

[17] Quarterly CCR data is available back to 2002 Q1, although credit institutions did not have to report default probabilities and credit commitments below €20,000 until 2012 Q2.

horizon.

Finally, we collect firm balance sheet and income statement data from the annual accounts (AA) reported annually by every limited liability firm in Belgium to the NBB. We supplement this data with confidential VAT declarations which offer more accurate measures of firm sales, investment, inputs, and materials expenditures.

Another distinguishing feature of our data is the availability of firm-level default probabilities assessed by lenders themselves. Regulation (EU) No 575/2013 of the European Parliament and the Council of 26 June 2013 sets out prudential requirements for credit institutions and investment firms in accordance to the Basel III guidelines.[18] It notably puts the ECB in charge of granting credit institutions permission to rely on the Internal Ratings Based (IRB) Approach instead of the Standardized Approach to assess their credit risk exposures subsequently used to set capital requirements. Credit institutions using the IRB approach subsequently report estimates of one-year ahead borrower-level default probabilities to the regulator.

One-year ahead default probabilities estimated by IRB credit institutions ideally proxies for firms unobserved true default risk. Being a primary input for the definition of banks' capital requirement, risk parameters estimated by IRB banks are subject to heavy scrutiny by the ECB and the European Banking Authority which have issued multiple guidelines to ensure the accuracy and robustness these default probabilities. Furthermore, we verify the forecasting power of these default probabilities to make sure that they capture realized default. Figure 3 shows the coefficient estimates of a regression of one-year ahead realized default on deciles of default probabilities. Default probabilities are strongly predictive of realized default, which confirms that the capture firm default risk adequately.[19]

2.2 Asymmetries Between Lenders and Borrowers

The Belgian corporate credit market is highly asymmetrical. On one hand, the supply of credit is concentrated. Out of 25 lenders in BECRIS, the largest four banks account for about 90% of total outstanding credit. Table 1 provides additional summary statistics on lenders. On average, banks have 12,700 borrowers, and operate in 54 NACE-2D divisions (out of 88).

[18] The IRB approach for risk-weighted exposures was first introduced by the Capital Requirement Directives 2006/48/EC and 2006/49/EC of the European Parliament and the Council of 14 June 2006.

[19] Note that the exponential shape of the coefficients is the result of the default probabilities being heavily skewed toward 0, so most deciles are tightly concentrated around low default probabilities.

On the other hand, the demand for corporate credit mostly emanates from small businesses. Table 2 presents firm-level summary statistics. Out of over 300,000 firms in the sample, the median firm is 14 years old, has €518,000 in assets, €67,000 in sales, and its EBIT is €32,000. It has no employees or capital expenditures. On the financing side, the median firm has been in a relationship with a single lender for five years. It has 1.5 outstanding debt contracts on average across all its lenders, totaling about €150,000, takes out a new contract every 10 months, and it is assigned a 0.7% probability of defaulting within the next year.[20]

The oligopolistic structure of the corporate credit market suggests that Belgian banks could derive market power from lending to firms. Moreover, small businesses might not be able to substitute bank lending with other forms of financing, as displayed by the limited display of alternative funding sources (e.g. only 108 firms issue public equity and 71 issue public debt).

2.3 Banks Hold Specialized Lending Portfolios

We measure lender industry specialization as a portfolio tilt toward a certain industry relative to a diversified benchmark. We follow Blickle, Parlatore and Saunders (2024) and define the specialization of bank b in sector s at time t as

$$\text{Spe}_{bst} = \frac{L_{bst}}{L_b} - \frac{L_{st}}{L_t} = \frac{L_{bst}}{\sum_{s' \in \mathcal{S}_b} L_{bs't}} - \frac{\sum_{b' \in \mathcal{B}_s} L_{b'st}}{\sum_{s' \in \mathcal{S}_b} \sum_{b' \in \mathcal{B}_s} L_{b's't}},$$

where L_{bst} is bank b's total outstanding credit to firms belonging to sector s, $\mathcal{S}_b$ is the set of sectors that bank b lends to, and $\mathcal{B}_s$ is the set of banks lending to sector s. A positive specialization means that the lender's portfolio is positively skewed toward that industry relative to the weight of the industry in total lending. A lender specialization of zero in a given industry means that its portfolio weight matches the industry size in aggregate lending, and we refer to this lender as being diversified in that industry. By definition, a lender's positive skew in a given industry is offset by negative portfolio skews in other industries. It also implies that other lenders must have negative skews in this industry. Finally, holding other lenders' size and specialization fixed, the industry specialization of a larger lender is mechanically smaller (an aspect we will account for in our analysis

[20] Relationship length is taken as the minimum inception date across all instruments between a firm and its lender. While it can be right censored due to some contracts having matured before the start of the BECRIS sample, it is not constrained by the sample period.

below).[21]

Specialization is scaled by the industry weight in total lending to adjust for the overall attractiveness of some industries affecting all lenders uniformly, such as general industry dynamism, low information acquisition costs, or low sector riskiness. In a similar spirit, Paravisini, Rappoport and Schnabl (2023) define a relative measure of specialization by dividing—instead of subtracting—the aggregate industry weight from the bank portfolio weight in that industry. They motivate the use of such specialization measures with a model of lender competition with heterogeneous lending capabilities across industries and show that measures based on outstanding credit capture these comparative advantages. While we rely on excess specialization throughout most of the analysis, we show that the results are also robust to using relative specialization.

We compute lender industry specialization at the NACE 2-digits, composed of 88 divisions,[22] to strike a balance between sufficient sectoral heterogeneity and noise from using an overly granular classification. To understand patterns of specialization, we begin by sorting each bank's portfolio in decreasing order of specialization and assign a rank to each industry in the lender's portfolio; the first rank goes to a lender's most preferred industry, and so on. We then average specializations across banks within each rank of specialization. Figure 1 plots the average specialization level within each rank in bank portfolios, split across the big four banks and the rest. Specialization is non-linear regardless of bank size; lenders disproportionately skew their portfolio toward a few industries. Smaller banks lend on average 20 percentage points more to their top industry relative to the size of that industry in total credit. Despite specialization being mechanically lower for large lenders, the big-four banks over-invest in their most preferred industry by three percentage points on average and do not hold diversified portfolio weights in their ten most preferred industries. Figure 2 shows the NACE 1-digit industry for each lender's top industry; the largest four banks specialize in industries related to trade, real estate, leisure, and skilled labor.

Thus, specialization is a widespread phenomenon in the Belgian corporate credit market. The propensity of large lenders to hold specialized portfolios suggests that it is not the result of a constrained choice of small lenders, but rather that specialization brings

[21] Dropping time subscripts, the sum of industries specializations across a lender's portfolio is zero: $\sum_{s\in\mathcal{S}_b} \text{Spe}_{bs} = \frac{\sum_{s\in\mathcal{S}_b} L_{bs}}{L_b} - \frac{\sum_{s\in\mathcal{S}_b} L_s}{L} = \frac{L_b}{L_b} - \frac{L}{L} = 0$. The average industry specialization across banks (weighted by the bank's contribution to total credit) is also zero: $\sum_{b\in\mathcal{B}_s} \text{Spe}_{bs} \frac{L_b}{L} = \sum_{b\in\mathcal{B}_s} \frac{L_{bs}}{L_b}\frac{L_b}{L} - \frac{\sum_{b\in\mathcal{B}_s} L_b}{L}\frac{L_s}{L} = \frac{L_s}{L} - \frac{L_s}{L} = 0$, which implies $\text{Spe}_{bs} = \frac{\sum_{b'\in\mathcal{B}_s\setminus\{b\}} w_{b'}\text{Spe}_{b's}}{w_b}$, where $w_b := \frac{L_b}{L}$.

[22] NACE 2-digits is comparable to NAICS 3-digits in the US composed of 99 sectors.

enough benefits to justify moving away from the diversified benchmark (Acharya, Hasan and Saunders, 2006). The mechanical effect of bank size on specialization also highlights the importance of bank-time fixed effects in empirical specifications. Looking at differences in industry specialization within the same bank prevents small lenders with high degrees of specialization from disproportionately weighing on the estimates and driving the results.

3 The Invest-Harvest Behavior of Specialized Banks

Section 2 established that the Belgian corporate credit market fits the environment described in Section 1 in which small businesses rely on specialized banks to build credit relationships. In this section, we provide empirical support for the conceptual framework's predictions and draw implications about the sources of bank specialization.

3.1 Empirical Strategy

We design our empirical framework to capture the pricing decisions of specialized banks outlined in predictions 1 and 2. While our data contains the entire stock of credit outstanding, we only use contracts at their time of inception or renegotiation. These credit flows capture active rate-setting decisions as opposed to passive moments in rates over a contract's life cycle—e.g., resulting from reference rate variations in the case of flexible rate contracts.[23] We estimate

$$\begin{aligned} R_{bfct} = {} & \alpha + \beta_0 \cdot RL_{bft} + \beta_1 \cdot \text{Spe}_{bs(f)t} + \beta_2 \cdot RL_{bft} \times \text{Spe}_{bs(f)t} \\ & + \beta_3 \cdot \mathbf{X}_{bfct} + \beta_4 \cdot \mathbf{X}_{bft} + \beta_5 \cdot \mathbf{X}_{ft-4} + \eta_{bc} + \eta_{bt} + \eta_{bf} + \varepsilon_{bfct}, \end{aligned} \tag{1}$$

where R_{bfct} denotes the interest rate—in basis points—on credit contract c charged by bank b to firm f, RL_{bft} is the relationship length, and $Spe_{bs(f)t}$ is our measure of excess bank specialization in sector s defined in Section 2.3.[24]

We narrow down interest rate variation coming from lender pricing behavior in three steps. First, we account for product differentiation. While credit lines and term loans are

[23] While our empirical specifications are estimated on credit flows, bank specialization is based on lenders' stock of outstanding credit to capture their cumulative industry experience.

[24] While the estimation sample runs between 2018 Q4 and 2023 Q4, a relationship start date is defined as the earliest origination date across all outstanding contracts between a lender and its borrower. Thus a relationship can be anterior to 2018, in fact, the 90th percentile relationship in our sample has been going for over 13 years.

standard contracts, they are tailored to borrowers' needs and risk profiles and eventually in their rates. $\mathbf{X}_{bfct}$ includes the contract's log-authorized credit amount and maturity. Furthermore, the vector of fixed effects η_{bc} controls for the contract's interest rate type, purpose, repayment rights, an origination vs. renegotiation indicator, and a collateralized vs. unprotected indicator, each interacted with bank fixed effects to allow for heterogeneous pricing practices across lenders.

Second, we account for borrower riskiness in $\mathbf{X}_{bft}$ using fixed effects for default probability deciles, since interest rate variation could be the result of changes in borrower risk premia throughout the relationship. While bank specialization is likely to be related to borrower riskiness through screening and monitoring, this empirical setup is only meant to capture lenders' pricing decisions for borrowers with similar riskiness.[25] We also include in $\mathbf{X}_{bft}$ the number of contracts and the credit outstanding between firm f and lender b. These stock variables control for differences in relationship intensity across specialized lenders which could affect the interest rate on subsequent contracts.

Third, as an equilibrium object, interest rates reflect borrowers' credit demand. In $\mathbf{X}_{ft-4}$, we leverage access to the balance sheets and income statements of even the smallest firms to control for an extensive set of firm characteristics affecting their credit demand, such as firm size (log-assets, deciles of firm age fixed effects, number of other lenders), liquidity (cash-over-assets, net working capital-over-assets, retained earnings-over-assets), capital structure (equity-over-liabilities), opacity (intangibles-over-assets), and profitability (EBIT-over-assets), all lagged one year.

In addition to absorbing aggregate time trends such as the current monetary policy environment, we use bank-time fixed effects (η_{bt}) to absorb any bank-level factor correlated with our measure of specialization, such as the effect of bank size on specialization documented in Figure 1. Therefore, parameters are estimated off variation in interest rates across firms from different industries borrowing from the *same* lender.

Relationship length is standardized and specialization is centered and scaled by the average specialization across banks' most preferred industries.[26] β_0 measures the effect on interest rates of a one-standard deviation increase in relationship length above the mean for borrowers in a diversified sector of the bank, while β_1 is the interest rate wedge for new relationships between borrowers in the lender's top industry and one of its diversified sectors. β_2 measures the wedge's dynamics as relationship length increases. Predictions 1 and 2 are verified if $\beta_1 < 0$ and $\beta_2 > 0$ respectively. Banks invest in new

[25] In Section 3.3, we decompose our results for different firm riskiness.

[26] The average top industry specialization is 13%.

relationships by giving lower rates to borrowers in their specialized industries ($\beta_1 < 0$) and harvest them later on by raising rates faster ($\beta_2 > 0$).

3.2 Results

Baseline. The baseline estimation results of specification (1) are reported in column (1) of Table 3. In the invest phase, lenders offer 22.3 b.p. lower rates to firms in their top industry of specialization compared to their diversified industries, a 13% discount over the median rate faced by borrowers in lenders' top industries. Given a median loan size, maturity, and EBIT among new borrowers in these top industries, this discount amounts to 4% of the median firm's annual EBIT.

In the harvest phase, lenders raise their rates 4.4 b.p. faster in their top industry over one-standard deviation longer relationships (from 6 to 12 years), a 69% steeper path relative to their diversified industries. We derive in Appendix B the relationship length threshold after which a firm currently borrowing from a bank's most preferred industry would face a lower rate by starting a new relationship with a diversified lender instead of signing its next contract with its incumbent lender. Borrowers would be better off switching after 13 years which is the case for about 15% of borrowers in lenders' top industries. Despite this harvest behavior, firms that belong to a bank's industry of specialization consistently get lower rates throughout its relationship. Our estimates predict that firms in lenders' top industries pay higher rates than borrowers in diversified industries after 32 years, which is less than 1% of borrowers.

In Table 4, we use contract maturity as outcome and report the results of our baseline specification in column (1). In the invest period, specialized lenders offer 4-month shorter contracts—4% shorter than the median maturity—in their top industries to avoid lower revenues. In the harvest period, lenders increase the relative maturity in their industry of specialization, which is consistent with the steeper rate increases in these industries. Thus, banks dynamically adjust contract maturity in a way that is consistent with their invest-harvest behavior.

In Figure 4, we examine the linearity of the previous results by splitting relationship length into quintiles in specification (1). Panel (a) and (b) show the effect of specialization on interest rates and maturity, respectively, estimated separately within each quintile of relationship length. The red markers refer to our baseline specifications with bank-time fixed effects only and the blue markers to specifications with bank-time and bank-firm fixed effects. As their relationship with their borrowers get longer, specialized banks monotonously charge higher rates and offer longer maturities.

Borrower selection and credit demand. A crucial concern about interpreting the previous results as evidence of the lending behavior of specialized banks is the non-random nature of credit relationships. Banks face heterogeneous borrower populations as a result of selected matching and attrition which could explain the differences observed across industries of specialization. For instance, lenders charge higher rates to riskier firms so the invest-harvest behavior could be the result of specialized banks matching with safer borrowers relative to non-specialized banks, and risky firms choosing to stay longer in relationships with specialized banks.[27] We address selected matching and selected attrition in two ways.

First, our extensive set of firm-level controls removes selection based on *observable* firm characteristics included in X_{ft-4}, such as size, profitability, liquidity, etc. Furthermore, firm-level default probabilities purge the estimates from differences in borrower riskiness across industries of specialization which we document in Sections 4.1 and 4.2.

Second, we address selection based on *unobservable* firm characteristics. In Table 3 columns (2) and (3) we augment specification (1) with bank-time and firm-time fixed effects respectively. Bank-firm fixed effects absorb relationship-level unobserved heterogeneity constant over time, such as lenders' expectations about borrower outcomes at the start of the relationship. In the spirit of Khwaja and Mian (2008), firm-time fixed effects absorb any firm-level unobserved heterogeneity affecting credit demand or borrower risk. We thus compare interest rates charged by multiple lenders with varying degrees of specialization throughout their relationship with the *same* borrower. While firm-time fixed effects identify lender behavior, it is not our preferred specification since it relies on firms with multiple credit relationships. This restriction overlooks the fact that 85% of firms in Belgium borrow from a single lender, mostly small businesses which are our primary object of study.

Overall, bank-firm and firm-time fixed effects do not change the sign nor magnitude of our coefficients which confirms that our results are not driven by selection or unobserved firm heterogeneity. Finally, our results on maturity are also robust to these fixed effects as shown in columns (2) and (3) of Table 4.

Robustness. We test the robustness of the dynamics of interest rates and contract maturities for specialized relationships along four main dimensions. First, in Table 5, we start from raw correlations and progressively add the controls in specification (1) to understand what shapes our results. Column (1) shows the interaction between relationship

[27] Risky firms could stay longer in a specialized relationship when they derive more value from their expertise, or if they face larger switching costs due to information asymmetries.

length and bank specialization without controls. These correlations given the opposite result which confirms that looking at rates alone is not sufficient to isolate lenders pricing behavior. Adding firm, contract, and relationship controls in column (2) uncovers lenders' invest behavior after accounting for heterogeneity in borrower credit demand and riskiness. The harvest behavior of specialized banks emerges in column (3) after adding bank-time fixed effects to control for bank-level factors correlated with bank industry specialization. In column (4), we add NACE 2D-by-time and province-by-time fixed effects to purge the estimates from industry-level and province-level factors affecting rates, relationships, and specialization.[28] In column (5) we verify the stability of our results to bank-time and bank-firm fixed effects. In Appendix Table C.2, we perform similar checks using contract maturity as outcome.

Second, in Table 6, we test the robustness of our result to alternative measures of specialization. In column (1), we drop the top 99th percentile of the distribution of specialization. While trimming extreme values may throw out some valuable variation about lenders' most preferred industries, we verify that our results are not driven by smaller banks which tend to have high levels of specialization as established in Section 2.3. In column (2) where we use Paravisini, Rappoport and Schnabl (2023)'s measure of relative specialization. This measure is derived from a model of lender competition with industry-specific advantage and scales the industry weights in a lender's portfolio by dividing—instead of subtracting—with industry size in total lending. In column (3), instead of a cardinal measure of specialization, we define an ordinal measure as the log-rank of an industry in a lender's portfolio sorted by decreasing order of specialization. In the invest phase, banks offer 1.1% lower rates in industries that are 1% better ranked in their portfolio. In the harvest phase, they raise rates 0.57% faster over a one-standard deviation longer relationship. In column (4), we control for geographical specialization to ensure that industry specialization stays relevant. Overall, the invest-harvest behavior is robust to various definitions of specialization.[29]

Third, we alleviate concerns about the results being driven by the COVID period. In April 2020, the Belgian government set out a corporate debt moratorium to foster liquidity provision. Eligible firms could apply for a six-month repayment deferral where only

[28] Being a bank-sector-time variable, bank specialization is not absorbed by bank-time and sector-time fixed effects. However, the heuristic interpretation of the results being identified off variation in specialization within a given bank of within a given sector does not hold here. The rigorous interpretation is that we are orthogonalizing variation in bank specialization with respect to any bank-time-level or sector-time-level variable (cf. Section 2 of Amiti and Weinstein (2018)).

[29] In Appendix Table C.3, we check the robustness of our results to alternative measures of specialization with contract maturity as outcome.

the loan principal was due while the loan duration was extended by the deferral period (Tielens, Piette and Jonghe, 2020). The moratorium was subsequently extended twice until June 30th, 2021. In column (1) of Appendix Table C.4 we estimate specification (1) by dropping the contracts subject to the debt moratorium (five percent of contracts). In column (2), we exclude the entire COVID period between April 2020 and June 2021 over which the moratorium was in effect. The results are robust to these alternative samples.

Fourth, in Appendix Table C.5 we test for the presence of invest-harvest behavior in the corporate credit register (CCR)—BECRIS' predecessor from 2012 to 2021 used below to study real outcomes—which reports the stock of outstanding credit at the bank-firm level. Given the lack of interest rates in this dataset, we use the firms' annual accounts to proxy for their average interest rates by taking the ratio of interest expenses to debt. We keep single-lender borrowers to avoid attributing these interest expenses to multiple lenders. Firms in a bank's top industry have lower, although not significantly, interest expenses early on compared to diversified-financed firms. Despite the coarseness of the data, we do find stronger evidence of harvest behavior by specialized banks for longer relationships. Furthermore, consistent with the results in Section 3.3, specialized banks exert stronger invest-harvest behavior on riskier firms.

3.3 Which Firms Are Exposed to the Invest-Harvest Behavior?

The invest-harvest behavior indicates that banks derive larger value from relationships in their industries of specialization. We provide further evidence of this channel by zooming within banks' preferred industries and analyzing which borrowers are the most exposed to the invest-harvest behavior. We decompose the dynamic behavior of specialized banks by estimating

$$\begin{aligned} R_{bfct} = \sum_{q=1}^{4} Q_q\{x_{bft}\} \times \Big(&\alpha_q + \beta_{0q} \cdot RL_{bft} + \beta_{1q} \cdot \text{Spe}_{bs(f)t} + \beta_{2q} \cdot RL_{bft} \times \text{Spe}_{bs(f)t}\Big) \\ &+ \beta_3 \cdot \mathbf{X}_{bfct} + \beta_4 \cdot \mathbf{X}_{bft} + \beta_5 \cdot \mathbf{X}_{ft-4} + \eta_{bc} + \eta_{bt} + \varepsilon_{bfct}, \end{aligned} \tag{2}$$

where x_{bft} is a firm or relationship-level characteristic. We focus on three dimensions of borrower heterogeneity. First, in Figure 5 we decompose the invest-harvest behavior by loan size using quartiles of contracts' authorized amounts. Second, in Figure 6 we use the number of outstanding contracts within the relationship and the firms total number of lenders as measures of relationship dependence. Third, in Figure 7 we split borrowers into quartiles of default probability to understand the role of firm riskiness.[30]

The coefficients $\{\beta_{1q}\}_{q=1}^{4}$ and $\{\beta_{2q}\}_{q=1}^{4}$ capture specialized lenders' differential invest-harvest behavior along x_{bft}. $\{\beta_{1q}\}_{q=1}^{4}$ are shown on the left-hand side panels of each figure in blue and measure lenders' rate differential charged to new relationships across their industries of specialization within each bin of x_{bft}. On the right-hand side panels, the estimates of $\{\beta_{2q}\}_{q=1}^{4}$ in red measure, for each bin of x_{bft}, the change in rates over a one-standard deviation increase in relationship length and across industries of specialization.

We find that specialized lenders give larger discounts in the invest phase toward riskier firms, firms with larger contracts, and firms that are more dependent on their credit relationships. Borrowers in lenders' preferred industries with authorized amounts larger than €201K get 30 b.p. lower rates than similar borrowers with contracts smaller than €20K. These discounts are concentrated among firms borrowing from less than three lenders, while borrowers with three or more lenders are charged similar rates regardless of industry specialization. Firms with default probabilities less than 0.4% also obtain similar rates regardless of their industry, while firms that belong to a lender's top industry with default probability above 2.4% get 50 b.p. lower rates early on.

In the harvest phase, specialized banks exert stronger holdup behavior on these risky, relationship-dependent firms with larger contracts. In contrast, firms with sub-€20K contracts, borrowing from more than two lenders, and with default probabilities less than 0.4% face similar rate increases regardless of their industry.

These results can be interpreted in light of the conceptual framework laid out in Section 1, where we established that specialized lenders exert invest-harvest behavior to attract and retain their most valued relationships. Risky, relationship-dependent firms who value their lender's expertise can be particularly locked in these specialized relationships, and stronger agency frictions might prevent them from switching to non-specialized lenders. Therefore, consistent with the evidence, specialized lenders attract these vulnerable borrowers by offering lower rates in the invest phase and take advantage of their higher switching costs by increasing rates faster in the harvest phase.

Robustness to alternative measures of firm riskiness. There might be concerns about comparing default probabilities assigned by lenders with different degrees of industry

[30] These specifications do not include firm-level fixed effects since we analyze differences in pricing behavior across borrowers. However, we showed in Section 3.1 that the invest-harvest behavior is robust to relationship selection and borrower credit demand. Besides, the results below are robust to the inclusion of industry-time and province-time fixed effects.

specialization. Specialized banks might have superior knowledge about their borrowers and assign consistently lower default probabilities than non-specialized lenders. We provide three ways to address this issue. First, we test for lender disagreement by estimating

$$PD_{bft} = \alpha + \sum_{q=1}^{10} \beta_{0q} \cdot Q_q \left\{ \text{Spe}_{bs(f)t} \right\} + \beta_1 \cdot \mathbf{X}_{bft} + \eta_{bt} + \eta_{ft} + \varepsilon_{bft},$$

where PD_{bft} is firm f's default probability assessed by bank b and $Q_q\{\text{Spe}_{bs(f)t}\}$ is the fixed effect for the qth decile of excess bank specialization in sector s. $\mathbf{X}_{bft}$ includes fixed effects for deciles of relationship length and deciles of authorized credit amounts to control non-parametrically for relationship characteristics affecting default probabilities. Bank-time fixed effects (η_{bt}) absorb bank-specific discrepancies unrelated to specialization, for instance resulting from differences in risk models. Importantly, we keep only firms borrowing from multiple lenders and use firm-time fixed effects (η_{ft}) to purge default probabilities from any firm characteristics, such as the firm's true underlying riskiness. Thus, the coefficients of interest plotted in Figure 8 are estimated off variation in default probabilities assigned by different lenders to the same firm. The Wald test statistics of 1.23 with p-value 0.27 confirms that the coefficients are not jointly different from each other meaning that lenders agree on their risk assessments.

Second, we use multiple predictive methods to estimate various alternative measures of firm riskiness independent of bank-related factors.[31] In column (1) of Appendix Table C.6, we obtain predicted default probabilities from an OLS regression using observed probabilities as dependent variable.[32] We also estimate default probabilities based on observed borrower financial distress. In columns (2) to (4), we estimate logit regressions using dummy variables equal to one if the borrower has a past due payment over 90 days, is expected to default, or is in forbearance, respectively. All of these predicted measures of firm riskiness support our result that specialized lenders exert stronger invest-harvest behavior on risky firms.

Third, in Appendix Table C.7, we proxy for firm riskiness using simple firm characteristics obtained from firms' financial statements and independent of banks judgment. We use EBIT-over-assets in column (1), sales-over-assets in column (2), net working capital-

[31] Specifically, we use as covariates NACE-4D-by-time and province-by-time fixed effects, relationship length, log-authorized amount, firm log-assets, firm age, number of lenders, debt-over-assets, cash-over-assets, net working capital-over-assets, intangibles-over-assets, EBIT-over-assets, and retained earnings-over-assets.

[32] OLS predicted values are not bounded by 0 and 1 so we use an inverse logistic transformation of the default probabilities as dependent variable and recover well-defined probabilities by applying a logistic transformation to the predicted values.

over-assets in column (3), cash-over-assets in column (4), and the firm's Altman Z-score in column (5). Again, firms with lower EBIT, sales, net working capital, cash, and Z-scores are subject to stronger invest-harvest behavior by specialized banks.

3.4 Borrower Responses to the Invest-Harvest Behavior

Specialized banks adjust their lending behavior throughout their relationships, which affects firms' decisions to borrow from these lenders. In line with prediction 3, we study the separation patterns of specialized relationships by estimating

$$\begin{aligned}\mathbb{1}\{\text{rel. ends}_{bft,t+4}\} = &\sum_{q=1}^{7} Q_q\{RL_{bft}\} \times \Big(\alpha_q + \beta_{0q} \cdot \text{Spe}_{bs(f)t}\Big) \\ &+ \beta_1 \cdot \mathbf{X}_{bft} + \beta_2 \cdot \mathbf{X}_{f0(b)} + \eta_{bt} + \eta_{s(f)t} + \eta_{p(f)t} + \varepsilon_{bft}, \end{aligned} \tag{3}$$

where $\mathbb{1}\{\text{rel. ends}_{bft,t+4}\}$ is an indicator variable equal to one if firm f ends its relationship with bank b within the next year, and $Q_q\{RL_{bft}\}$ is the fixed effect for the qth septile of relationship length.[33] We draw our estimation sample from the Corporate Credit Register (CCR) to benefit from the longer sample period (2012 Q2-2021 Q4) and since our outcome of interest is at the bank-firm level. We keep relationships with no past-due payments reported at the time of termination to capture firm separation decisions outside of financial distress. The specification includes relationship and firm controls as well as industry-time and province-time fixed effects to isolate separation decisions in response to lenders' invest-harvest behavior. Relationship controls ($\mathbf{X}_{bft}$) are default probability deciles, log-outstanding credit, and the number of outstanding contracts. Firm-level controls ($\mathbf{X}_{f0(b)}$) are the total number of lenders, log-assets, equity-over-liabilities as well as cash, intangibles, net working capital, retained earnings, EBIT, sales, all scaled over assets. Firm characteristics are measured at the beginning of the relationship to account for borrower selection.

Figure 9 plots the coefficient estimates for $\{\beta_{0q}\}_{q=1}^{7}$. The effect of borrowing from a specialized lender on relationship endings is nonlinear over the course of a lending relationship. Firms that belong to the bank's most preferred industries are three percentage points less likely at first to end a relationship relative to firms in a diversified sector of a bank's portfolio. This wedge closes as the relationship goes on and eventually reverts; after five years of relationship, specialized-financed firms are four percentage points *more* likely to end their relationship than diversified-financed firms. As relationship length in-

[33] We adjust the number of quantiles to capture the full dynamic of separations while avoiding noise.

creases further, the positive gap between specialized and diversified-financed firms closes again, until both types of firm end up with the same propensity to separate from their lender.

These separation patterns are consistent with the invest-harvest behavior of specialized banks affecting relationship terminations. In the invest phase, specialized-financed firms benefit from advantageous credit conditions and are more likely to stick with their current lender. As specialized banks enter their harvesting phase, their borrowers become relatively more likely to end their relationships. The peak occurs around five years, which is before the ten-year threshold computed in Section 3.1 after which specialized-financed firms would be better off starting a new relationship with a diversified lender. Firms that persist in their relationship are the ones with the highest switching costs, thus becoming increasingly less likely to separate from their lenders as years go by.

Next, we test the heterogeneous separation patterns across varying degrees of firm riskiness. We estimate

$$\begin{aligned}\mathbb{1}\{\text{rel. ends}_{bft,t+4}\} = \sum_{q=1}^{7} Q_q\{RL_{bft}\} \times \Big(&\alpha_q + \beta_{0q} \cdot \ln(PD_{bft}) + \beta_{1q} \cdot \text{Spe}_{bs(f)t} \\ &+\beta_{2q} \cdot \ln(PD_{bft}) \times \text{Spe}_{bs(f)t}\Big) \\ &+ \beta_3 \cdot \mathbf{X}_{bft} + \beta_4 \cdot \mathbf{X}_{f0(b)} + \eta_{bt} + \eta_{s(f)t} + \eta_{p(f)t} + \varepsilon_{bft}, \end{aligned} \tag{4}$$

and plot the coefficient estimates for $\{\beta_{1q}\}_{q=1}^{7}$ and $\{\beta_{2q}\}_{q=1}^{7}$ in Figure 10. The baseline effect of relationship length on separation for risky firms in panel (a) is similar to the one described in Figure 9. In panel (b), we observe that riskier firms are always relatively less likely to end their relationship with a specialized lender. The effect is stronger for short and long durations, but weaker for relationship lengths or about five years. The lower separation rates of risky firms for new relationships are consistent with these borrowers receiving more beneficial treatment from specialized lenders in the invest phase. Moreover, low separation rates for long-standing relationships also suggest that risky borrowers face larger switching costs, and justifies why specialized lenders exert stronger invest-harvest behavior toward these vulnerable firms.

Differences in the relationship length of risky firms could be the result of moral hazard preventing these firms from switching to a new less informed lender, forcing them to stay in their current relationship. Risky firms might also benefit more from the monitoring services offered by specialized lenders, leading to fewer defaults compared to risky firms borrowing from non-specialized banks.

The selection of risky firms with specialized banks poses a threat to the study of bank pricing strategies since part of the observed differences in rates charged by specialized lenders could be explained by specialized banks asking for higher risk premia to their borrowers. Thus, access to firm-level default probabilities is a key aspect of addressing these sample selection concerns.

4 Do Firms Benefit From Bank Specialization?

The invest-harvest behavior of specialized banks established in Section 3 is consistent with firms facing larger costs of switching away from a relationship with a specialized lender. In this section, we show that these switching costs can be interpreted as opportunity costs of losing the benefits from a relationship with a specialized lender. In other words, borrowing from a specialized bank is not a zero-sum game between the firm and its lender. While lenders extract more surplus from the firms in the industries that they specialize in, firms also derive larger surpluses as a result of their relationship with a specialized lender.

4.1 Risky Firms Sort With Specialized Banks

We first focus on relationship formation and document that riskier firms are more likely to start a relationship with a specialized lender. We build a dataset of bank-firm matches by expanding our sample of new relationships to allow firms in a given industry to choose among any lender that formed at least one new relationship in an industry over a given quarter,[34] and estimate

$$\mathbb{1}\{\text{Rel. start}_{bft}\} = \alpha + \beta_0 \cdot x_{ft-4} + \beta_1 \cdot \text{Spe}_{bs(f)t} + \beta_2 \cdot x_{ft-4} \times \text{Spe}_{bs(f)t} + \eta_{bt} + \eta_{s(f)t} + \eta_{p(f)t} + \varepsilon_{bft},$$

where $\mathbb{1}\{\text{Rel. start}_{bft}\}$ is an indicator variable equal to one if firm f matches with bank b, and x_{ft-1} stands for various firm characteristics affecting the likelihood of a match with a specialized bank. We use the firm's Altman Z-score, equity-over-liabilities, cash-over-assets, net working capital-over-assets, intangibles-over-assets, return on assets, and retained earnings-over-assets, all lagged one year. Bank-time fixed effects (η_{bt}) account for

[34] Since we do not observe loan applications, no outside option (i.e., picking none of the active lenders) is included to avoid making arbitrary choices about which firm is looking to form a new relationship. Thus, every firm ends up finding a match and in this context adding firm characteristics as controls does not bear any meaningful interpretation.

the baseline matching probability of a firm with a given lender, and sector-time ($\eta_{s(f)t}$) and province-time ($\eta_{p(f)t}$) fixed effects control for the general ability of firms in specific industries or locations to form new relationships. The coefficient β_1 is the baseline effect of an increase in lender specialization on the match probability, and β_2—the coefficient of interest—measures the differential effect of the firm characteristic x_{ft-4} on the match probability with a specialized bank.

Table 7 reports the estimation results. In column (1), we see that risky firms with a mean Z-score are 1.2 percentage points more likely to match with a bank if they belong to their top industry of specialization relative to industries where the bank is diversified. A one-standard deviation increase in the firm's Z-score above its mean is associated with a 0.08 percentage point reduction in the probability of a firm matching with a specialized bank. While specialized banks have overall higher match probabilities, we find in columns (2) to (7) that firms with lower equity, cash, net working capital, EBIT, and retained earnings, and firms with higher intangible assets are all relatively more likely to match with a specialized bank. Besides, note that while risky firms are more likely to match with specialized banks than safer firms, it is not at odds with Section 3.3 which shows that lenders assign similar default probabilities regardless of the degree of specialization. The latter results hold conditional on a given firm matching with multiple lenders.

One might attribute the higher propensity of risky firms to match with a specialized lender as coming from the lack of lender alternatives. Less credit-worthy firms might also suffer from stronger search frictions and be unaware of the presence of other, less specialized lenders in their industry, or they might be credit-rationed by less specialized lenders that lack the information technology to effectively screen high-risk borrowers. However, search frictions and adverse selection would reduce lender competition and give specialized lenders greater market power before a match occurs, which is at odds with these lenders offering larger rate discounts to riskier borrowers at the start of their relationship. Instead, the positive sorting of between risky firms and specialized banks suggests that firms are willing to engage into relationships with specialized lenders despite their invest-harvest behavior.

4.2 Risky Firms Have Longer Relationships With Specialized Lenders

Turning to relationship terminations, we collapse the time dimension of our sample and keep bank-firm relationships with an observed end date and no reported past-due payments. We estimate

$$
\begin{aligned}
\text{Overall RL}_{bf} = \alpha + \beta_0 \cdot \ln(PD_{bfT}) + \beta_1 \cdot \text{Spe}_{bs(f)0} + \beta_2 \cdot \ln(PD_{bfT}) \times \text{Spe}_{bs(f)0} \\
+ \beta_3 \cdot \mathbf{X}_{bfT} + \beta_4 \cdot \mathbf{X}_{f0(b)} + \eta_{bT} + \eta_{s(f)T} + \eta_{p(f)T} + \varepsilon_{bf}, \qquad (5)
\end{aligned}
$$

where $Overall\ RL_{bf}$ is the overall relationship length in years between bank b and firm f, and PD_{bfT} is the firm default probability at the end of the relationship. Relationship controls ($\mathbf{X}_{bfT}$) are log-authorized and log-maturity credit at the time of separation, and firm controls measured at the beginning of the relationship ($\mathbf{X}_{f0(b)}$) include log-assets, firm age deciles, equity-over-liabilities as well as cash, intangibles, net working capital, retained earnings, EBIT, and sales, all scaled by assets.

Estimation results are reported in Table 8. Borrowers with a one percent default probability separate on average four months later from their lender if they belong to their lender's top industry of specialization compared to a diversified industry.[35] A one-percent increase in default probability is associated with a two-month delay in the separation time for firms belonging to the bank's top industry. Thus, while we showed in Section 3.4 that the invest-harvest behavior of specialized banks is associated with more frequent relationship terminations, overall, specialized lenders have longer relationships with their borrowers and even more so with risky ones. The ability of specialized lenders to retain relationships for longer helps understand why they are able to provide larger initial discounts to their borrowers. They expect to subsequently extract surplus from them for longer, which raises the overall value of a relationship from the lender's perspective.

4.3 The Real Effects of Bank Specialization

We showed in Section 3.1 that banks extract more surplus from their borrowers for relationships that they establish in their industry of specialization. Do firms benefit from staying in a relationship with a specialized lender as well? We estimate

$$
\begin{aligned}
\Delta y_{ft,0(b)} = \alpha + \beta_0 \cdot RL_{bft} + \beta_1 \cdot \text{Spe}_{bs(f)t} + \beta_2 \cdot RL_{bft} \times \text{Spe}_{bs(f)t} \\
+ \beta_3 \cdot \mathbf{X}_{bft} + \beta_4 \cdot \mathbf{X}_{f0(b)} + \eta_{bt} + \eta_{s(f)t} + \eta_{p(f)t} + \varepsilon_{bft}, \qquad (6)
\end{aligned}
$$

where $\Delta y_{ft,0(b)}$ is a measure of firm outcome growth over the course of the relationship with its lender. Using growth rates removes concerns about specialized banks sorting with certain types of borrowers as documented in Section 4.1. Relationship controls ($\mathbf{X}_{bft}$)

[35] The average total relationship length is 4.3 years in this sample.

are default probability deciles, log-outstanding credit, and the number of outstanding contracts., and firm controls are identical to specification (1) but measured at the start of the relationship.

Table 9 reports the estimation results using as outcomes change in earnings-over-assets (column 1), change in retained earnings-over-assets (column 2), cash reserved growth (column 3), change in equity-over-assets (column 4), change in net working capital-over-assets (column 5), change in net trade credit-over-assets (column 6). Firms that borrow from specialized banks have higher growth in all of the previous outcomes over the length of their relationship. In particular, note that earnings are net of interest payments, so specialized-financed firms are more profitable despite being held up more strongly by their lender.

These estimates might be confounded by borrower selection into longer relationships with specialized lenders based on some firm characteristic. For instance, firms with high profit-growth potential might select into long relationships with specialized banks only, for a reason independent of the bank's degree of specialization. We augment specification (6) and replace industry-by-time and province-by-time fixed effects with bank-firm relationship fixed effects. The effect of specialization on firm outcomes is now identified within a given bank-firm relationship off variation in the bank specialization level in the firm industry over time. [36] Thus, the results are not driven by compositional changes in the sample of borrowers across industries that the banks specialized in. The estimation results are reported in Appendix Tables C.9 and C.8.

5 Conclusion

We study the interplay between bank specialization and relationship lending, two strategies used by credit institutions to mitigate information asymmetries with opaque borrowers. We use contract-level data on the universe of corporate credit in Belgium to capture lending to small businesses at a granular level and leverage firm balance sheet data available for every limited liability company in Belgium to study the real effects of bank specialization.

Specialized lenders dynamically adjust their interest rates to attract and retain borrowers. They attract borrowers early on by offering lower rates than non-specialized lenders and raise them faster once their relationships are established. This invest-harvest

[36] We do not need to use growth rates anymore since the outcome's initial value is absorbed by the relationship fixed effect.

behavior is consistent with specialized banks having greater market power over established relationships. Despite their harvesting behavior, we find evidence that specialized banks benefit from lower lending costs, as they charge consistently lower rates throughout their relationships.

Lenders exert stronger invest-harvest behavior on riskier firms that rely heavily on their credit relationships. The invest-harvest behavior affects the sorting of firms and borrowers, as riskier firms are more likely to match and stay longer in relationships with specialized lenders. We are the first to establish that firms in specialized relationships have better growth in real outcomes as measured by firm growth in sales, return-on-assets, investment, and equity value.

By providing credit to risky firms at the early stages of their relationship, specialized banks help alleviate the credit constraints weighing on the most vulnerable businesses. Thus, the recent push for open banking policies increasing information sharing across financial institutions could have undesirable effects. By reducing banks' informational advantages over their borrowers, these open banking policies could weaken lenders' incentives to develop expertise *ex ante* through specialization.

Table 1: Summary Statistics: Banks

	Mean	SD	Pctl 10	Med	Pctl 90
Panel A: credit stock					
Credit outstanding (€M)	9431.77	18378.02	38.00	742.00	40545.00
N borrowers (in K)	12.72	20.99	0.00	3.00	53.00
N contracts (in K)	28.71	49.37	0.00	4.00	125.00
NACE-2D industries	54.34	23.72	16.00	63.00	80.00
Reports default prob. (%)	85.44	24.63	46.00	98.00	100.00
Panel B: credit flows					
Credit originations (€M)	673.81	1804.18	1.00	26.00	2169.00
N borrowers	1606.71	3050.45	5.00	266.00	6631.00
N contracts	2037.70	3986.57	6.00	311.00	7878.00

Notes: This table reports summary statistics between 2018 Q4 and 2023 Q4 for the sample of banks used in Section 3. *NACE-2D industries* is the number of industries that a bank lends to in a given quarter (out of 88 NACE-2D divisions). *Reports default prob.* is the share of borrowers for which a given lender reports a default probability in a given quarter, conditional on that lender reporting at least one probability. In panel A, *N contracts* is the number of outstanding contracts held by a lender in a given quarter and *N borrowers* is the number of firms a lender has a relationship with. In panel B, *N contracts* is the number of contracts originated by a lender in a given quarter and *N borrowers* is the number of borrowers these new contracts go to. Quarterly sample sourced from BECRIS, Belgium's AnaCredit (cf. Appendix A.2).

Table 2: Firms Summary Statistics: Firms

	Mean	SD	Pctl 10	Med	Pctl 90	Pctl 99
Panel A: balance sheet						
Assets (K€)	3601.40	209507.30	96.20	517.70	3509.00	30386.30
Cash in hand (K€)	222.80	2704.00	2.00	43.40	359.90	2495.80
NWC / assets (%)	-141.10	92131.20	-29.70	12.60	61.00	89.70
Intangibles / assets (%)	1.80	8.10	0.00	0.00	1.20	47.60
Equity / liabilities (%)	385.50	121302.50	0.50	54.00	329.50	1916.80
Altman Z-score	0.40	4679.20	-0.00	1.00	2.80	8.00
Firm age (years)	16.70	12.50	3.20	14.00	33.20	54.00
Panel B: income statement						
Sales (K€)	473.40	11808.00	9.50	67.20	605.90	5502.30
Employees (FTE)	5.60	73.70	0.00	0.00	8.00	65.00
EBIT (K€)	118.20	4070.70	-18.10	31.60	244.90	1635.40
CapEx (K€)	29.00	806.90	0.00	0.00	31.00	322.00
Retained / assets (%)	-176.00	143396.20	0.00	0.00	12.40	36.50
Inputs / assets (%)	303.10	146704.40	0.70	12.10	54.10	149.40
Materials / assets (%)	111.70	40407.10	0.00	3.40	39.00	125.00
Payroll / assets (%)	14.80	6575.00	0.00	0.00	9.10	34.70
Panel C: relationship with lender						
N lenders	1.20	0.40	1.00	1.00	2.00	3.00
Rel. length (years)	6.30	5.30	1.00	4.80	13.60	24.30
Years last contract	1.40	2.30	0.10	0.80	3.10	12.20
N contracts outstanding	2.20	2.50	1.00	1.50	4.00	10.00
Credit outstanding (K€)	595.60	5255.20	16.50	150.00	1000.00	6571.20
Credit originations (K€)	380.00	3491.30	7.50	40.00	500.00	5947.40
Default probability (%)	3.70	13.40	0.10	0.70	5.10	100.00
Panel D: credit contract characteristics						
Interest rate (%)	2.30	2.70	0.90	1.80	4.40	6.80
Authorized amount (K€)	319.50	2034.20	12.00	68.00	512.70	3975.00
Maturity remaining (years)	4.30	19.70	0.20	2.70	11.60	19.10

Notes: Table reports summary statistics between 2018 Q4 and 2023 Q4 for the sample of firms used in Section 3. See Appendix A.1 for variables construction. Quarterly credit data sourced from BECRIS, Belgium's AnaCredit (cf. Appendix A.2); annual firm balance sheets and income statements from the Annual Accounts; sales, capital expenditure, and inputs data from firms VAT declarations; employment data from firms social security declarations.

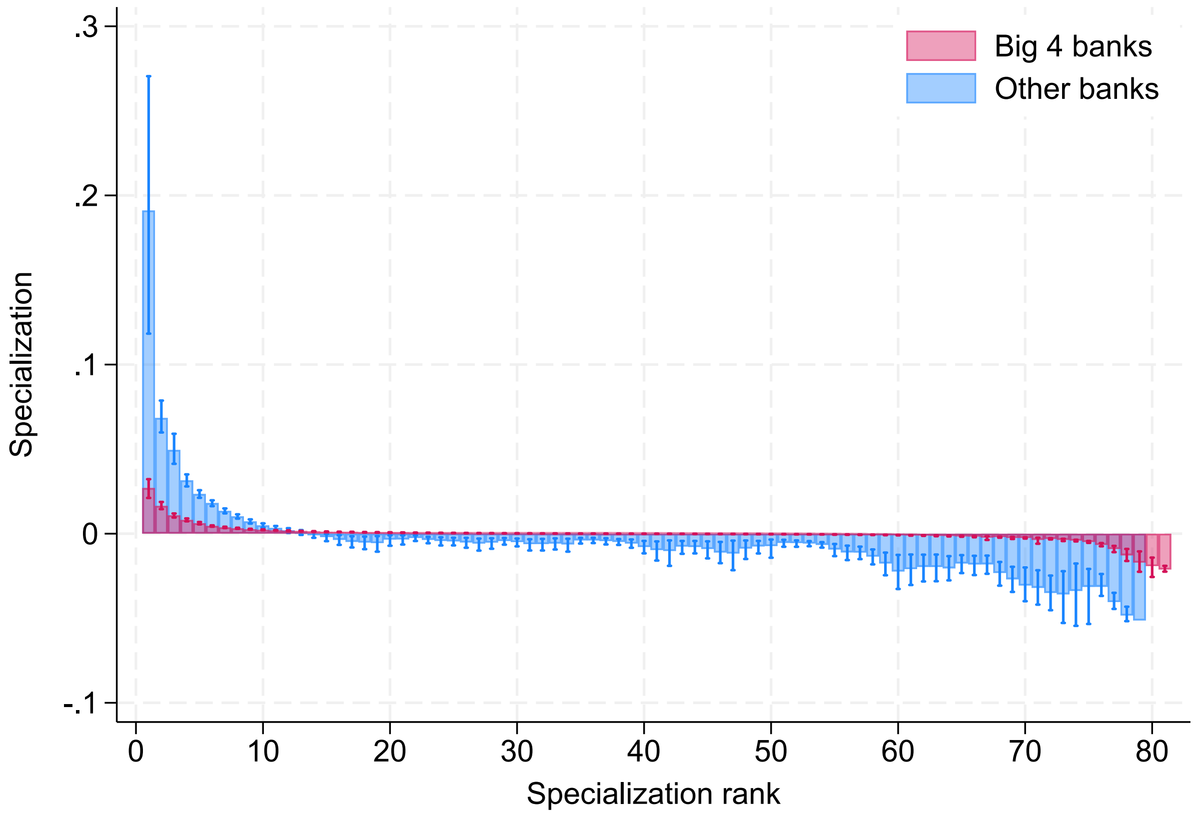


Figure 1: Average Specialization Split by Rank in Bank Portfolios

Notes: This figure plots average industry specialization within each rank industries hold in banks' lending portfolios, where excess specialization is defined in Section 2.3. In red are the four largest Belgian banks and in blue the remaining banks. Vertical lines are bootstrapped 95% confidence intervals clustered at the bank-by-NACE 2D level using 1000 replications each. Quarterly bank-NACE 2D sample between 2018 Q4 and 2023 Q4 taken from BECRIS, Belgium's AnaCredit (cf. Appendix A.2).

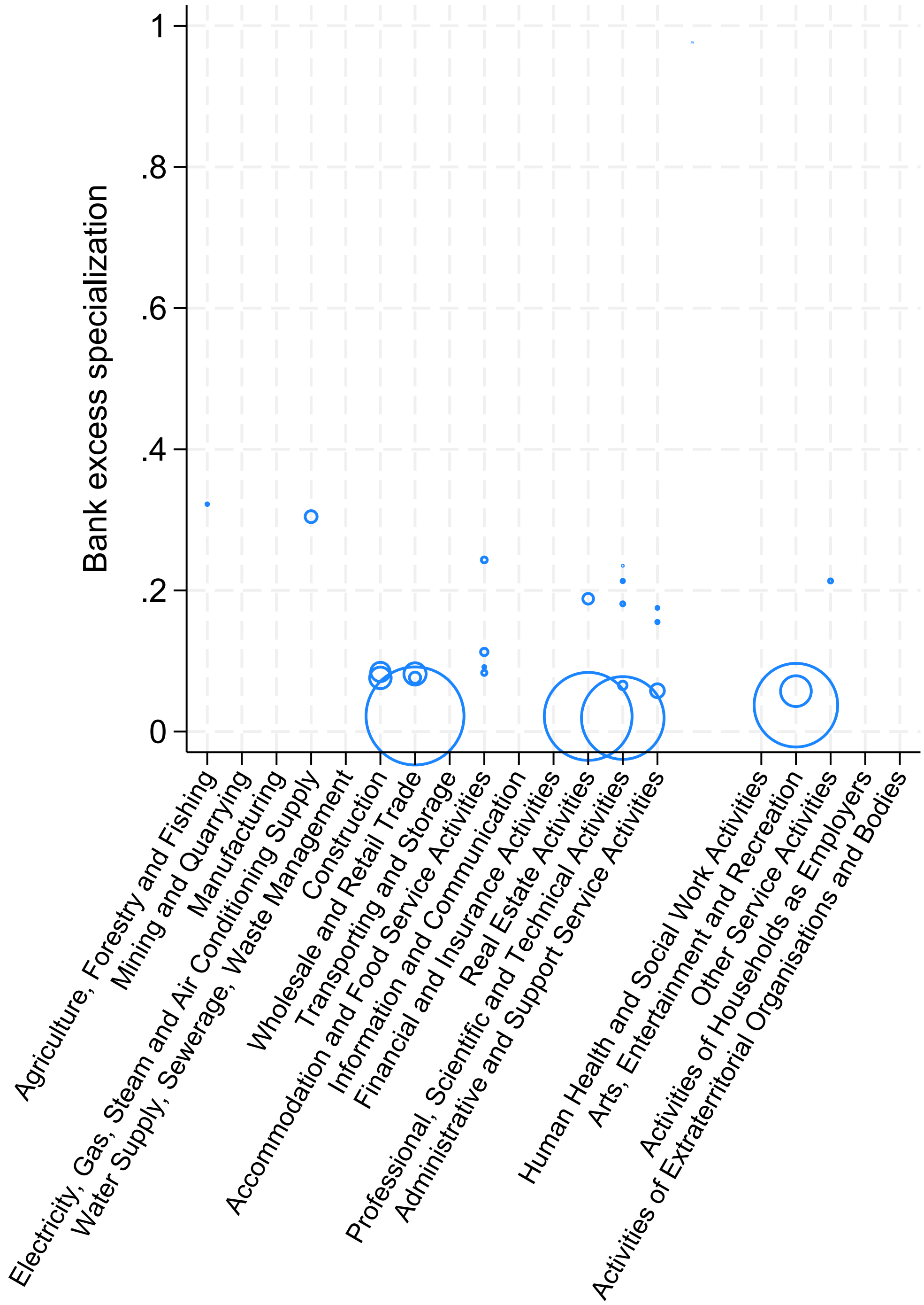


Figure 2: Banks Most Preferred Industries

Notes: Figure plots banks excess specialization in their most preferred NACE-2D division industry classified along NACE-1D sections, where excess specialization is defined in Section 2.3. Bubbles are proportional to bank overall size. Quarterly bank-NACE 2D sample between 2018 Q4 and 2023 Q4 and sourced from BECRIS, Belgium's AnaCredit (cf. Appendix A.2).

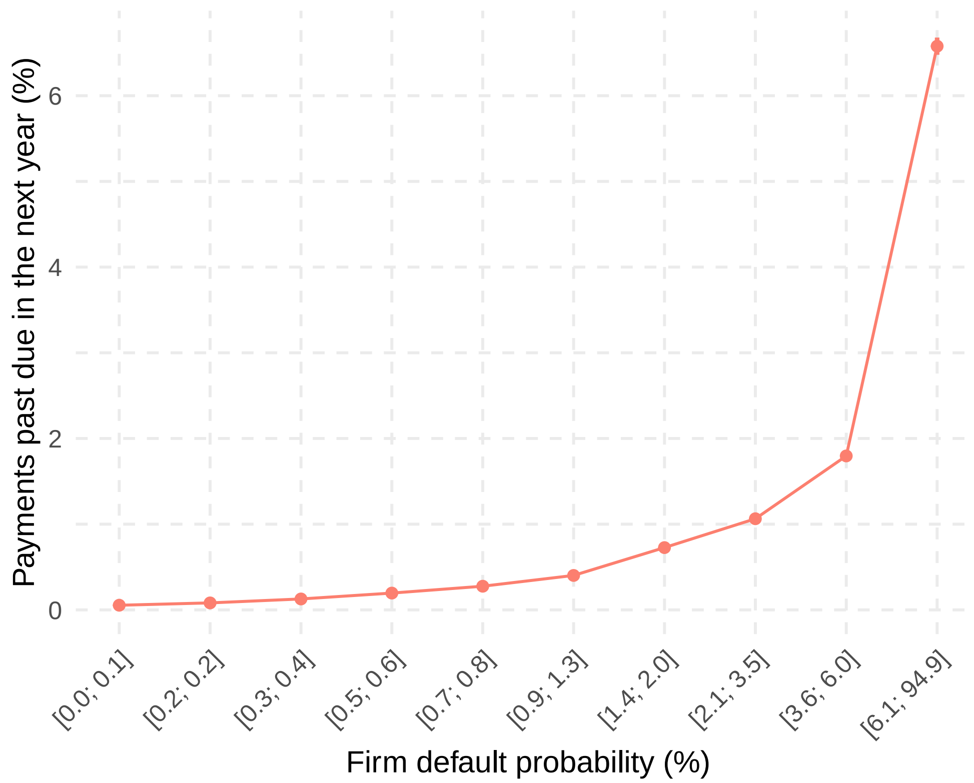


Figure 3: Assessed Default Probabilities Predict Realized Past Due Payments

Notes: Figure plots estimated coefficients for $\{\beta_q\}_{q=1}^{10}$ from:

$$\mathbb{1}\{\text{Past due}_{bft,t+4}\} = \sum_{q=1}^{10} \beta_q \cdot Q_q \left\{PD_{bft}\right\} + \varepsilon_{bft},$$

where $\mathbb{1}\{\text{Past due}_{bft,t+4}\}$ is an indicator equal to one with firm f has a past due payment within the next year, and $Q_q\{PD_{bft}\}$ is the fixed effect for the qth decile of firm default probabilities. Estimation sample is a quarterly panel of bank-firm relationships from the Belgian Corporate Credit Register (CCR) over the period 2012 Q2 to 2021 Q4 using term loans and credit lines (cf. Appendix A.2). Only observations prior to default are kept, with default probabilities less than 95%. Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 3: The Invest-Harvest Behavior of Specialized Banks

Outcome		R_{bfct}	
	(1)	(2)	(3)
RL_{bft}	6.4***	8.4	2.0***
	(0.30)	(17.4)	(0.76)
$\text{Spe}_{bs(f)t}$	-22.3***	-23.5***	-13.1*
	(2.4)	(6.4)	(7.6)
$RL_{bft} \times \text{Spe}_{bs(f)t}$	4.4**	7.8**	7.9*
	(1.8)	(3.0)	(4.7)
Contract controls	Yes	Yes	Yes
Relationship controls	Yes	Yes	Yes
Firm controls	Yes	Yes	
Bank-time FEs	Yes	Yes	Yes
Bank-firm FEs		Yes	
Firm-time FEs			Yes
Observations	502,298	441,863	287,404
Adjusted R^2	0.61	0.77	0.87

Notes: Table reports estimated coefficients of interest from:

$$R_{bfct} = \alpha + \beta_0 \cdot RL_{bft} + \beta_1 \cdot \text{Spe}_{bs(f)t} + \beta_2 \cdot RL_{bft} \times \text{Spe}_{bs(f)t} + \beta_3 \cdot \mathbf{X}_{bfct} + \beta_4 \cdot \mathbf{X}_{bft} + \beta_5 \cdot \mathbf{X}_{ft-4} + \eta_{bc} + \eta_{bt} + \eta_{bf} + \varepsilon_{bfct},$$

where R_{bfct} is the interest rate in basis points charged by bank b to firm f for credit contract c at time t, RL_{bft} is the relationship length between firm f and bank b, and $Spe_{bs(f)t}$ is a measure of excess bank specialization in sector s defined in Section 2.3. Specialization is centered and scaled by the average top sector specialization across banks and RL_{bft} is scaled by its standard deviation. Contract controls ($\mathbf{X}_{bfct}$) are log-authorized credit and contract maturity. Relationship controls ($\mathbf{X}_{bft}$) are default probability deciles, log-outstanding credit, and the number of outstanding contracts. Firm-level controls ($\mathbf{X}_{ft-4}$) are total number of lenders, log-assets, cash/assets, intangibles/assets, net working capital/assets, equity/liabilities, retained earnings/assets, EBIT/assets, sales/assets, all lagged one year, and firm age deciles. Bank-contract-level fixed effects (η_{bc}) are interest rate type, instrument purpose, instrument repayment rights, origination vs. renegotiation indicator, and a collateralized indicator, all interacted with bank fixed effects (cf. Appendix A.1). Quarterly contract-level estimation sample uses credit lines and term loans at origination and renegotiation from IRB banks between 2018 Q4 and 2023 Q4. Sourced from BECRIS, Belgium's AnaCredit (cf. Appendix A.2). Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

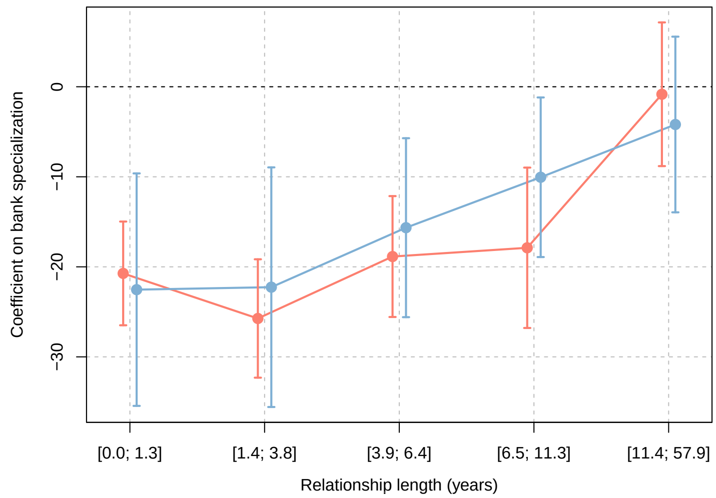
Table 4: Dynamics of Contract Maturities Across Levels of Specializations

Outcome	Matur_{bfct}		
	(1)	(2)	(3)
RL_{bft}	-0.06***	-3.2***	-0.07***
	(0.006)	(0.50)	(0.02)
$\text{Spe}_{bs(f)t}$	-0.18***	-0.37***	-0.90***
	(0.06)	(0.13)	(0.24)
$RL_{bft} \times \text{Spe}_{bs(f)t}$	0.16***	0.11*	0.35***
	(0.04)	(0.07)	(0.13)
Contract controls	Yes	Yes	Yes
Relationship controls	Yes	Yes	Yes
Firm controls	Yes	Yes	
Bank-time FEs	Yes	Yes	Yes
Bank-firm FEs		Yes	
Firm-time FEs			Yes
Observations	502,298	441,863	287,404
Adjusted R^2	0.49	0.65	0.69

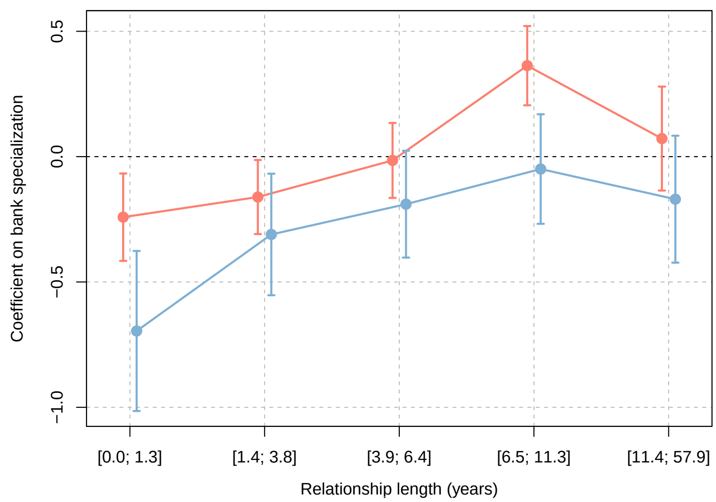
Notes: Table reports estimated coefficients of interest from:

$$\begin{aligned}\text{Matur}_{bfct} = \alpha + \beta_0 \cdot RL_{bft} + \beta_1 \cdot \text{Spe}_{bs(f)t} + \beta_2 \cdot RL_{bft} \times \text{Spe}_{bs(f)t} \\ + \beta_3 \cdot \mathbf{X}_{bfct} + \beta_4 \cdot \mathbf{X}_{bft} + \beta_5 \cdot \mathbf{X}_{ft-4} + \eta_{bc} + \eta_{bt} + \eta_{bf} + \varepsilon_{bfct},\end{aligned}$$

where $Matur_{bfct}$ is the maturity in years of contract c between bank b to firm f at time t, RL_{bft} is the relationship length between firm f and bank b, and $Spe_{bs(f)t}$ is a measure of excess bank specialization in sector s defined in Section 2.3. Specialization is centered and scaled by the average top sector specialization across banks and RL_{bft} is scaled by its standard deviation. Contract controls ($\mathbf{X}_{bfct}$) are log-authorized credit and contract maturity. Relationship controls ($\mathbf{X}_{bft}$) are default probability deciles, log-outstanding credit, and the number of outstanding contracts. Firm-level controls ($\mathbf{X}_{ft-4}$) are total number of lenders, log-assets, cash/assets, intangibles/assets, net working capital/assets, equity/liabilities, retained earnings/assets, EBIT/assets, sales/assets, all lagged one year, and firm age deciles. Bank-contract-level fixed effects (η_{bc}) are interest rate type, instrument purpose, instrument repayment rights, origination vs. renegotiation indicator, and a collateralized indicator, all interacted with bank fixed effects (cf. Appendix A.1). Quarterly contract-level estimation sample uses credit lines and term loans at origination and renegotiation from IRB banks between 2018 Q4 and 2023 Q4. Sourced from BECRIS, Belgium's AnaCredit (cf. Appendix A.2). Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.



(a) Interest Rates



(b) Maturity

Figure 4: The Invest-Harvest Behavior of Specialized Banks

Notes: Figure plots estimated coefficients for $\{\beta_{1q}\}_{q=1}^{5}$ from:

$$y_{bfct} = \alpha + \sum_{q=1}^{5} \beta_{0q} \cdot Q_q\{RL_{bft}\} + \sum_{q=1}^{5} \beta_{1q} \cdot Q_q\{RL_{bft}\} \times \text{Spe}_{bs(f)t}$$
$$+ \beta_2 \cdot \mathbf{X}_{bfct} + \beta_3 \cdot \mathbf{X}_{bft} + \beta_4 \cdot \mathbf{X}_{ft-4} + \eta_{bc} + \eta_{bt} + \eta_{bf} + \varepsilon_{bfct},$$

where y_{bfct} is the interest rate in basis points charged by bank b to firm f for credit contract c at time t in panel (a) and the contract maturity in panel (b). $Q_q\{RL_{bft}\}$ is the fixed effect for the qth quintile of relationship length, and $Spe_{bs(f)t}$ is a measure of excess bank specialization in sector s defined in Section 2.3. Specialization is centered and scaled by the average top sector specialization across banks. Contract controls ($\mathbf{X}_{bfct}$, η_{bc}), relationship controls ($\mathbf{X}_{bft}$), and firm controls ($\mathbf{X}_{ft-4}$) are identical to Table 3. Red coefficient specifications use bank-time fixed effects, blue coefficient specifications include bank-time and bank-firm fixed effects. Quarterly contract-level estimation sample uses credit lines and term loans at origination and renegotiation from IRB banks between 2018 Q4 and 2023 Q4. Sourced from BECRIS, Belgium's AnaCredit (cf. Appendix A.2). Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 5: Invest-Harvest Behavior: Robustness to Fixed Effects

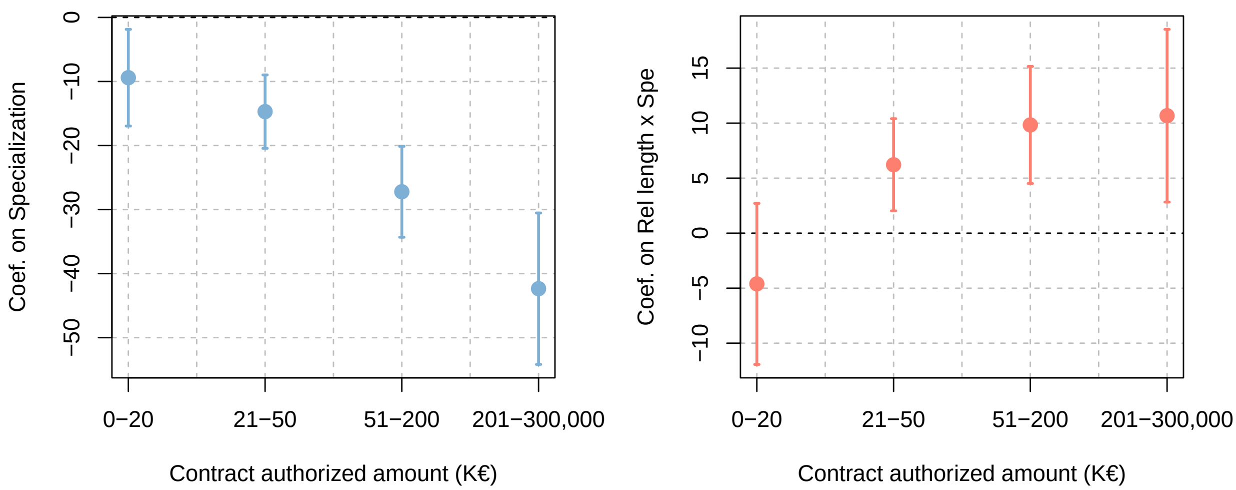
Outcome	R_{bfct}				
	(1)	(2)	(3)	(4)	(5)
RL_{bft}	13.0***	16.3***	6.4***	6.1***	8.4
	(0.38)	(0.39)	(0.30)	(0.30)	(17.4)
$\text{Spe}_{bs(f)t}$	6.9**	-15.5***	-22.3***	-18.5***	-23.5***
	(3.1)	(3.2)	(2.4)	(2.3)	(6.4)
$RL_{bft} \times \text{Spe}_{bs(f)t}$	-13.9***	0.70	4.4**	4.4**	7.8**
	(2.5)	(2.5)	(1.8)	(1.7)	(3.0)
Firm controls		Yes	Yes	Yes	Yes
Contract controls		Yes	Yes	Yes	Yes
Relationship controls		Yes	Yes	Yes	Yes
Bank-time FEs			Yes	Yes	Yes
(NACE & Prov)-time FEs				Yes	
Bank-firm FEs					Yes
Observations	700,213	502,304	502,298	502,234	441,863
Adjusted R^2	0.008	0.11	0.61	0.62	0.77

Notes: Table reports estimated coefficients of interest from variations of specification (1), where R_{bfct} is the interest rate in basis points charged by bank b to firm f for credit contract c at time t, RL_{bft} is the relationship length between firm f and bank b, $Spe_{bs(f)t}$ is a measure of excess bank specialization in sector s defined in Section 2.3, and PD_{bft} is firm f's default probability assessed by bank b. Specialization is centered and scaled by the average top sector specialization across banks and RL_{bft} is scaled by its standard deviation. Contract controls ($\mathbf{X}_{bfct}$) are log-authorized credit and contract maturity. Relationship controls ($\mathbf{X}_{bft}$) are default probability deciles, log-outstanding credit, and the number of outstanding contracts. Firm-level controls ($\mathbf{X}_{ft-4}$) are total number of lenders, log-assets, cash/assets, intangibles/assets, net working capital/assets, equity/liabilities, retained earnings/assets, EBIT/assets, sales/assets, all lagged one year, and firm age deciles. Bank-contract-level fixed effects (η_{bc}) are interest rate type, instrument purpose, instrument repayment rights, origination vs. renegotiation indicator, and a collateralized indicator, all interacted with bank fixed effects (cf. Appendix A.1). Quarterly contract-level estimation sample uses credit lines and term loans at origination and renegotiation from IRB banks between 2018 Q4 and 2023 Q4. Sourced from BECRIS, Belgium's AnaCredit (cf. Appendix A.2). Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 6: Invest-Harvest Behavior: Robustness to Measures of Specialization

Outcome	R_{bfct}			
	(1)	(2)	(3)	(4)
Sample	Drop 99th	Relative	-log(Rank)	Geo. spe.
RL_{bft}	8.2	11.3	12.2	8.7
	(17.4)	(17.5)	(17.5)	(17.4)
$\text{Spe}_{bs(f)t}$	-12.3***	-98.7***	-1.1***	-23.5***
	(3.3)	(22.2)	(0.36)	(6.4)
$\text{Geo spe}_{bp(f)t}$				5.9
				(5.2)
$RL_{bft} \times \text{Spe}_{bs(f)t}$	4.1***	30.6**	0.57**	7.6**
	(1.6)	(13.7)	(0.22)	(3.0)
$RL_{bft} \times \text{Geo spe}_{bp(f)t}$				4.5
				(3.3)
Contract controls	Yes	Yes	Yes	Yes
Relationship controls	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Bank-time FEs	Yes	Yes	Yes	Yes
Bank-firm FEs	Yes	Yes	Yes	Yes
Observations	441,823	441,863	441,863	441,863
Adjusted R^2	0.77	0.77	0.77	0.77

Notes: Table reports estimated coefficients of interest from specification (1), where R_{bfct} is the interest rate in basis points charged by bank b to firm f for credit contract c at time t, RL_{bft} is the relationship length between firm f and bank b. RL_{bft} is scaled by its standard deviation. $Spe_{bs(f)t}$ refers to various measures of bank industry specialization. Column (1) drops the top 99th percentile of excess specialization ($\frac{L_{bs}}{L_b} - \frac{L_s}{L}$), column (2) uses relative specialization ($\frac{L_{bs}}{L_b} / \frac{L_s}{L}$), column (3) uses (minus) the log-rank of each industry sorted by decreasing order of specialization in their portfolio (Rank($Spe_{bs} \mid s \in \mathcal{S}_b$)), and column (4) uses both excess industry specialization and bank excess geographical specialization in province p ($Spe_{bp} = \frac{L_{bp}}{L_b} - \frac{L_p}{L}$). In all columns but (3), specialization measures are centered and scaled by the average top sector specialization across banks. Contract controls ($\mathbf{X}_{bfct}$) are log-authorized credit and contract maturity. Relationship controls ($\mathbf{X}_{bft}$) are default probability deciles, log-outstanding credit, and the number of outstanding contracts. Firm-level controls ($\mathbf{X}_{ft-4}$) are total number of lenders, log-assets, cash/assets, intangibles/assets, net working capital/assets, equity/liabilities, retained earnings/assets, EBIT/assets, sales/assets, all lagged one year, and firm age deciles. Specifications include bank-by-time and bank-by-firm fixed effects. Bank-contract-level fixed effects (η_{bc}) are interest rate type, instrument purpose, instrument repayment rights, origination vs. renegotiation indicator, and a collateralized indicator, all interacted with bank fixed effects (cf. Appendix A.1). Quarterly contract-level estimation sample uses credit lines and term loans at origination and renegotiation from IRB banks between 2018 Q4 and 2023 Q4. Sourced from BECRIS, Belgium's AnaCredit (cf. Appendix A.2). Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.



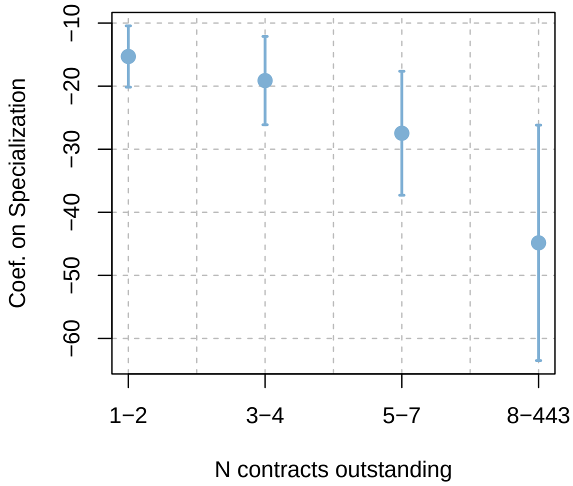
(a) New Relationships (b) Established Relationships

Figure 5: Large Contracts Are Subject to Stronger Invest-Harvest

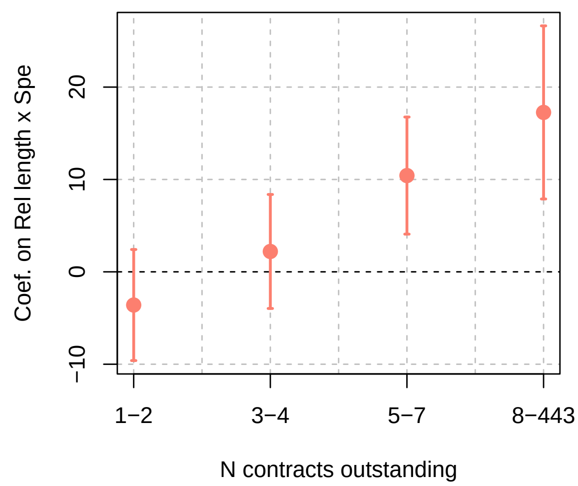
Notes: Figure plots estimated coefficients for $\{\beta_{1q}\}_{q=1}^{4}$ from:

$$R_{bfct} = \sum_{q=1}^{4} Q_q\{L_{bfct}\} \times \left(\alpha_q + \beta_{0q} \cdot RL_{bft} + \beta_{1q} \cdot \text{Spe}_{bs(f)t} + \beta_{2q} \cdot RL_{bft} \times \text{Spe}_{bs(f)t}\right)$$
$$+ \beta_3 \cdot \mathbf{X}_{bfct} + \beta_4 \cdot \mathbf{X}_{bft} + \beta_5 \cdot \mathbf{X}_{ft-4} + \eta_{bc} + \eta_{bt} + \varepsilon_{bfct},$$

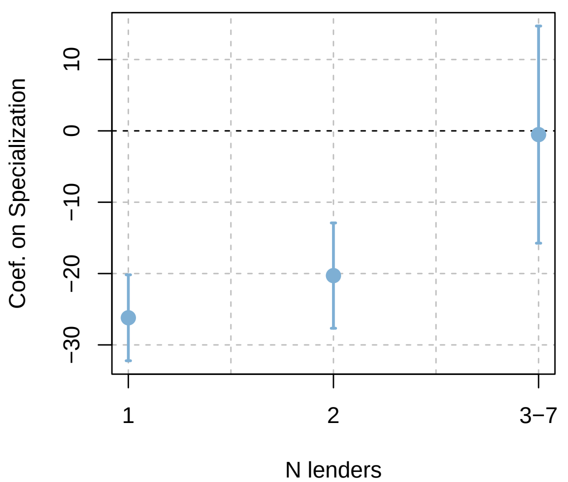
where $Q_q\{L_{bfct}\}$ is the fixed effect for the qth quartile of contract c's authorized amount. R_{bfct} is the interest rate in basis points charged by bank b to firm f for credit contract c at time t, RL_{bft} is the relationship length between firm f and bank b, $Spe_{bs(f)t}$ is a measure of excess bank specialization in sector s defined in Section 2.3. Specialization is centered and scaled by the average top sector specialization across banks and RL_{bft} is scaled by its standard deviation. Contract controls ($\mathbf{X}_{bfct}$) are log-authorized credit and contract maturity. Relationship controls ($\mathbf{X}_{bft}$) are log-outstanding credit, and the number of outstanding contracts. Firm-level controls ($\mathbf{X}_{ft-4}$) are total number of lenders, log-assets, cash/assets, intangibles/assets, net working capital/assets, equity/liabilities, retained earnings/assets, EBIT/assets, sales/assets, all lagged one year, and firm age deciles. Specification includes bank-by-time and bank-by-firm fixed effects. Bank-contract-level fixed effects (η_{bc}) are interest rate type, instrument purpose, instrument repayment rights, origination vs. renegotiation indicator, and a collateralized indicator, all interacted with bank fixed effects (cf. Appendix A.1). Quarterly contract-level estimation sample uses credit lines and term loans at origination and renegotiation from IRB banks between 2018 Q4 and 2023 Q4. Sourced from BECRIS, Belgium's AnaCredit (cf. Appendix A.2). Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.



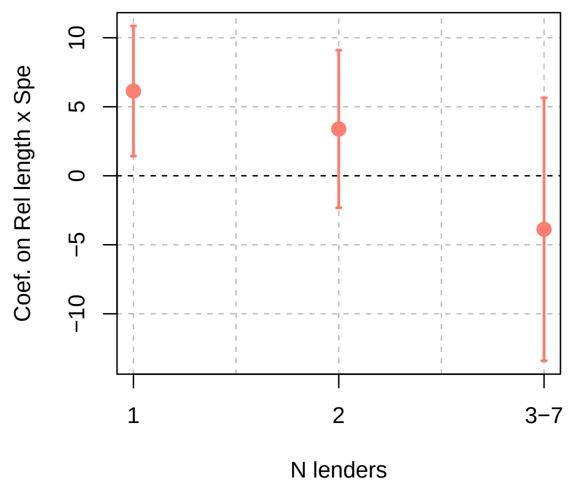
(a) New Relationships



(b) Established Relationships



(c) New Relationships



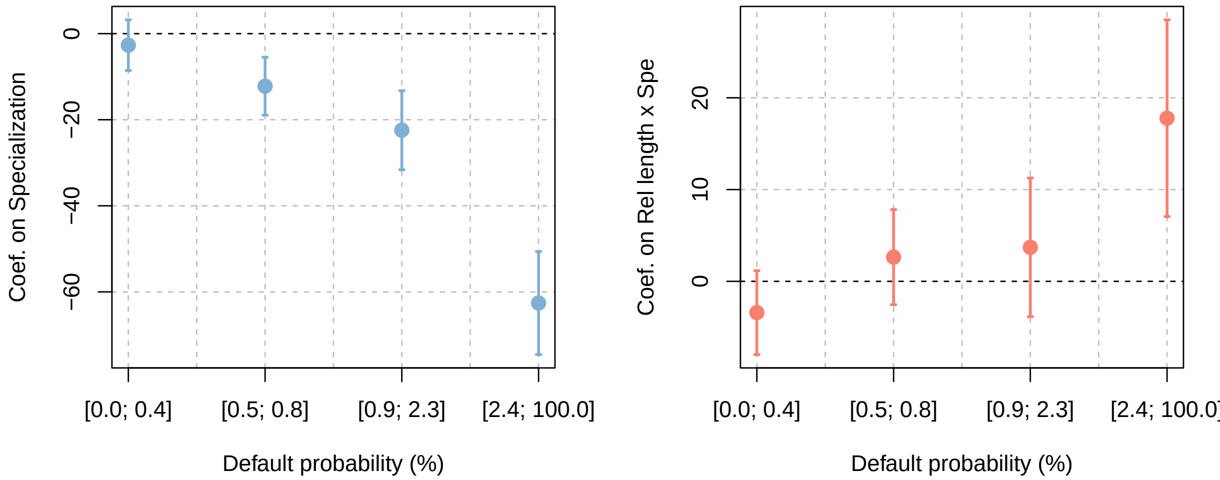
(d) Established Relationships

Figure 6: Relationship-Dependent Firms Are Subject to Stronger Invest-Harvest

Notes: Figure plots estimated coefficients for $\{\beta_{1q}\}_{q=1}^{4}$ from:

$$R_{bfct} = \sum_{q=1}^{4} Q_q\{x_{bft}\} \times \left(\alpha_q + \beta_{0q} \cdot RL_{bft} + \beta_{1q} \cdot \text{Spe}_{bs(f)t} + \beta_{2q} \cdot RL_{bft} \times \text{Spe}_{bs(f)t}\right)$$
$$+ \beta_3 \cdot \mathbf{X}_{bfct} + \beta_4 \cdot \mathbf{X}_{bft} + \beta_5 \cdot \mathbf{X}_{ft-4} + \eta_{bc} + \eta_{bt} + \varepsilon_{bfct},$$

where $Q_q\{x_{bft}\}$ is the fixed effect for the qth quartile of the number of outstanding contracts between firm f and bank b and the qth tercile firm f's number of lenders in the first and second line, respectively. R_{bfct} is the interest rate in basis points charged by bank b to firm f for credit contract c at time t, RL_{bft} is the relationship length between firm f and bank b, $Spe_{bs(f)t}$ is a measure of excess bank specialization in sector s defined in Section 2.3. Specialization is centered and scaled by the average top sector specialization across banks and RL_{bft} is scaled by its standard deviation. Contract controls ($\mathbf{X}_{bfct}$) are log-authorized credit and contract maturity. Relationship controls ($\mathbf{X}_{bft}$) are log-outstanding credit, and the number of outstanding contracts. Firm-level controls ($\mathbf{X}_{ft-4}$) are total number of lenders, log-assets, cash/assets, intangibles/assets, net working capital/assets, equity/liabilities, retained earnings/assets, EBIT/assets, sales/assets, all lagged one year, and firm age deciles. Specification includes bank-by-time and bank-by-firm fixed effects. Bank-contract-level fixed effects (η_{bc}) are interest rate type, instrument purpose, instrument repayment rights, origination vs. renegotiation indicator, and a collateralized indicator, all interacted with bank fixed effects (cf. Appendix A.1). Quarterly contract-level estimation sample uses credit lines and term loans at origination and renegotiation from IRB banks between 2018 Q4 and 2023 Q4. Sourced from BECRIS, Belgium's AnaCredit (cf. Appendix A.2). Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.



(a) New Relationships

(b) Established Relationships

Figure 7: Risky Firms Are Subject to Stronger Invest-Harvest

Notes: Figure plots estimated coefficients for $\{\beta_{1q}\}_{q=1}^{4}$ from:

$$R_{bfct} = \sum_{q=1}^{4} Q_q\{PD_{bft}\} \times \left(\alpha_q + \beta_{0q} \cdot RL_{bft} + \beta_{1q} \cdot \text{Spe}_{bs(f)t} + \beta_{2q} \cdot RL_{bft} \times \text{Spe}_{bs(f)t}\right)$$
$$+ \beta_3 \cdot \mathbf{X}_{bfct} + \beta_4 \cdot \mathbf{X}_{bft} + \beta_5 \cdot \mathbf{X}_{ft-4} + \eta_{bc} + \eta_{bt} + \varepsilon_{bfct},$$

where $Q_q\{PD_{bft}\}$ is the fixed effect for the qth quartile of firm default probability. R_{bfct} is the interest rate in basis points charged by bank b to firm f for credit contract c at time t, RL_{bft} is the relationship length between firm f and bank b, $Spe_{bs(f)t}$ is a measure of excess bank specialization in sector s defined in Section 2.3. Specialization is centered and scaled by the average top sector specialization across banks and RL_{bft} is scaled by its standard deviation. Contract controls ($\mathbf{X}_{bfct}$) are log-authorized credit and contract maturity. Relationship controls ($\mathbf{X}_{bft}$) are log-outstanding credit, and the number of outstanding contracts. Firm-level controls ($\mathbf{X}_{ft-4}$) are total number of lenders, log-assets, cash/assets, intangibles/assets, net working capital/assets, equity/liabilities, retained earnings/assets, EBIT/assets, sales/assets, all lagged one year, and firm age deciles. Specification includes bank-by-time and bank-by-firm fixed effects. Bank-contract-level fixed effects (η_{bc}) are interest rate type, instrument purpose, instrument repayment rights, origination vs. renegotiation indicator, and a collateralized indicator, all interacted with bank fixed effects (cf. Appendix A.1). Quarterly contract-level estimation sample uses credit lines and term loans at origination and renegotiation from IRB banks between 2018 Q4 and 2023 Q4. Sourced from BECRIS, Belgium's AnaCredit (cf. Appendix A.2). Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

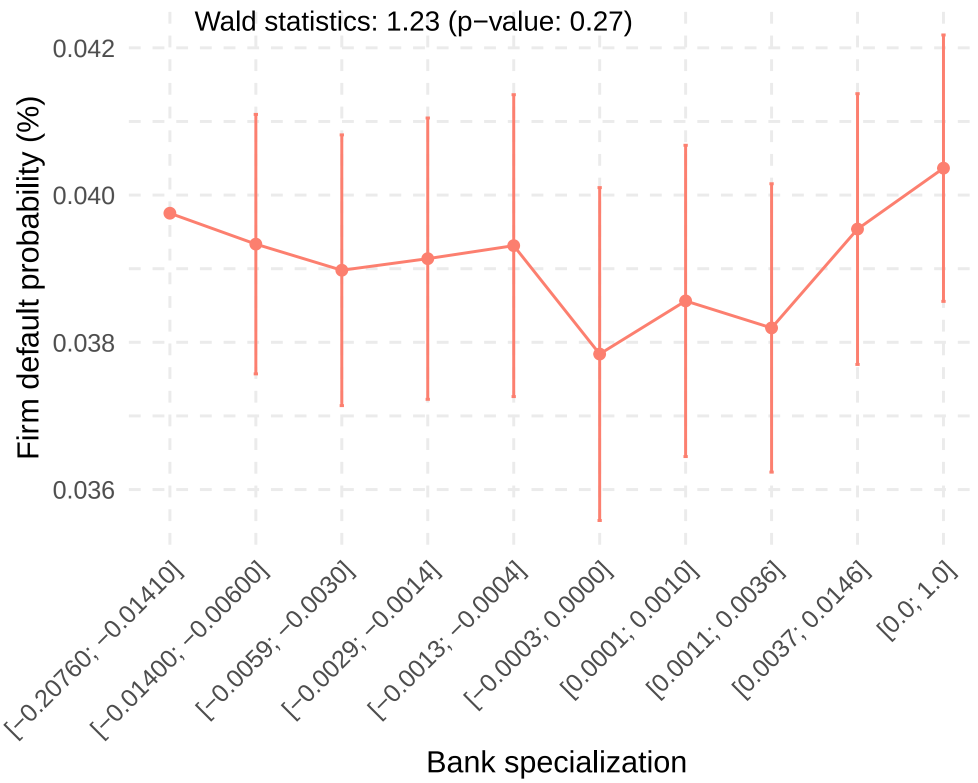


Figure 8: Banks Assign Similar Default Probabilities Regardless of Specialization

Notes: Figure plots estimated coefficients for $\{\beta_{0q}\}_{q=1}^{10}$ from:

$$PD_{bft} = \alpha + \sum_{q=1}^{10} \beta_{0q} \cdot Q_q \left\{ \text{Spe}_{bs(f)t} \right\} + \beta_1 \cdot \mathbf{X}_{bft} + \eta_{bt} + \eta_{ft} + \varepsilon_{bft},$$

where PD_{bft} is firm f's default probability assessed by bank b, $Q_q\{\text{Spe}_{bs(f)t}\}$ is the fixed effect for the qth decile of excess bank specialization in sector s, and $\mathbf{X}_{bft}$ includes fixed effects of relationship length deciles and authorized credit amounts deciles. Specification includes bank-by-time, and firm-by-time fixed effects. The plotted fixed effects are scaled by the constant. Reported is the Wald test statistics of joint nullity of the decile fixed effects of bank industry specialization (before scaling by the constant). Estimation sample is a quarterly panel of bank-firm relationships from the Belgian Corporate Credit Register (CCR) over the period 2012 Q2 to 2021 Q4 using term loans and credit lines (cf. Appendix A.2). Firms with at least two lenders and no payments past due are kept. Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

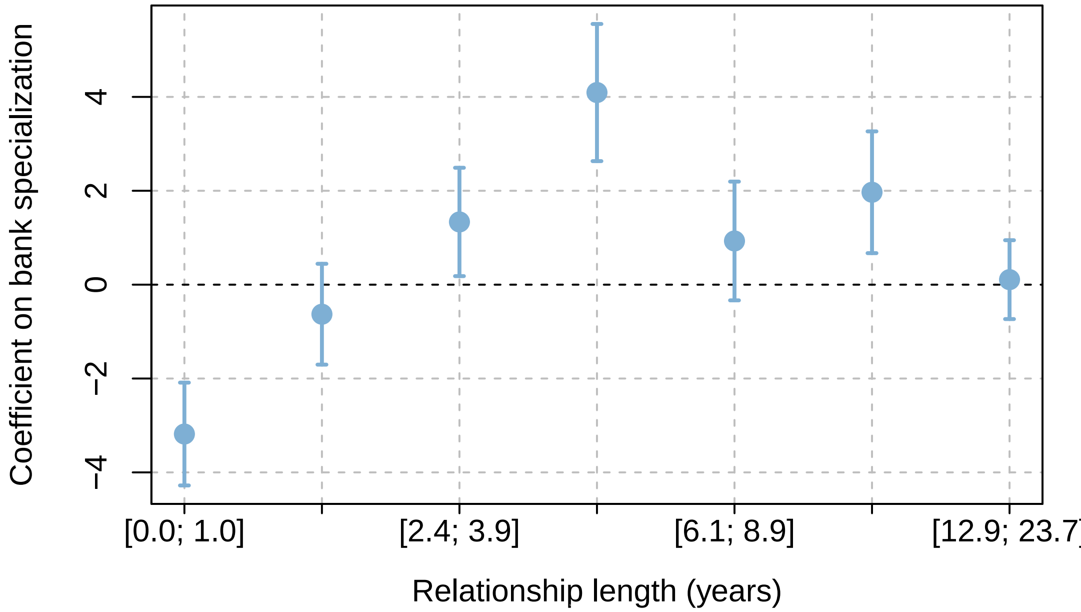
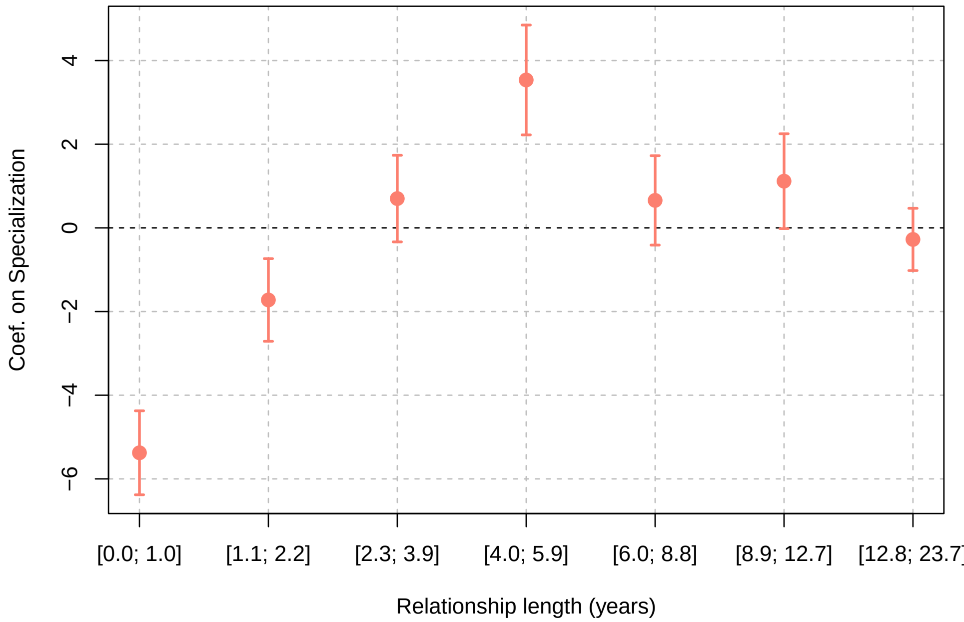


Figure 9: Effect of Invest-Harvest Behavior on Relationship Separations

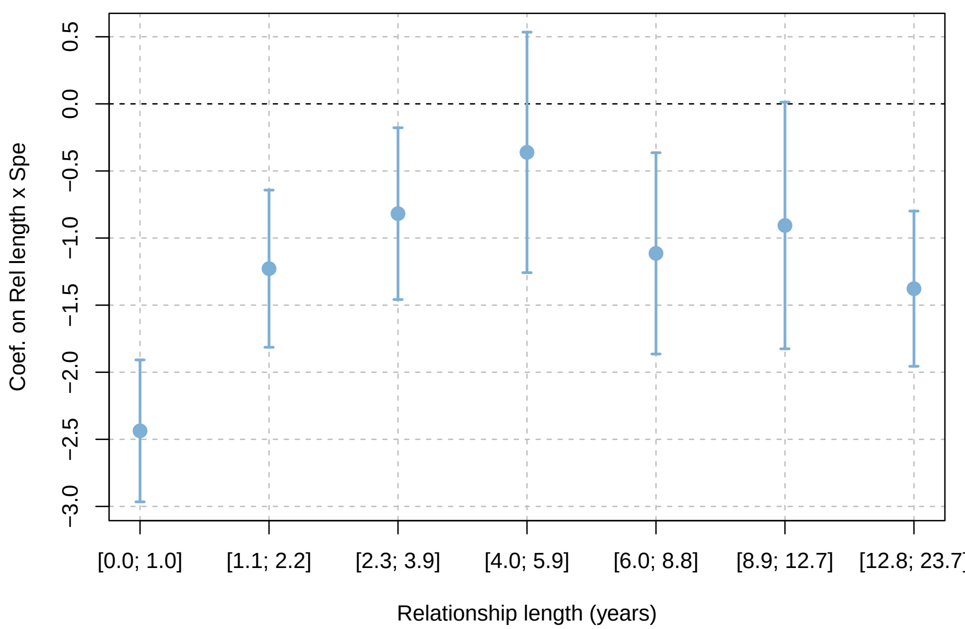
Notes: Figure plots estimated coefficients for $\{\beta_{0q}\}_{q=1}^{7}$ from:

$$\mathbb{1}\{\text{rel. ends}_{bft,t+4}\} = \sum_{q=1}^{7} Q_q\{RL_{bft}\} \times \left(\alpha_q + \beta_{0q} \cdot \text{Spe}_{bs(f)t}\right) + \beta_1 \cdot \mathbf{X}_{bft} + \beta_2 \cdot \mathbf{X}_{f0(b)} + \eta_{bt} + \eta_{s(f)t} + \eta_{p(f)t} + \varepsilon_{bft},$$

where $\mathbb{1}\{\text{rel. ends}_{bft,t+4}\}$ is an indicator variable equal to one if the firm f ends its relationship with bank b within the next year, and $Q_q\{RL_{bft}\}$ is the fixed effect for the qth septile of relationship length. $Spe_{bs(f)t}$ is a measure of excess bank specialization in sector s defined in Section 2.3. Specialization is centered and scaled by the average top sector specialization across banks. Relationship controls ($\mathbf{X}_{bft}$) are log-firm default probability, log-outstanding credit, and log-collateral. Firm-level controls ($\mathbf{X}_{f0(b)}$) are total number of lenders, firm age deciles, log-assets, cash/assets, intangibles/assets, net working capital/assets, equity/liabilities, retained earnings/assets, EBIT/assets, sales/assets, all measured at the beginning of the relationship. Specifications include bank-by-time and bank-by-firm fixed effects. Estimation sample is a quarterly panel of bank-firm relationships from the Belgian Corporate Credit Register (CCR) over the period 2012 Q2 to 2021 Q4 using term loans and credit lines (cf. Appendix A.2). We keep only relationship terminations for firms where no past due payments are reported. Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.



(a) Safe Firms



(b) Risky Firms

Figure 10: Effect of Invest-Harvest Behavior on Relationship Separations

Notes: Figure shows estimated coefficients of interest for specification (4) where $\mathbb{1}\{\text{rel. ends}_{bft,t+4}\}$ is an indicator variable equal to one if the firm f ends its relationship with bank b within the next year, and $Q_q\{RL_{bft}\}$ is the fixed effect for the qth septile of relationship length. $Spe_{bs(f)t}$ is a measure of excess bank specialization in sector s defined in Section 2.3. Specialization is centered and scaled by the average top sector specialization across banks. Relationship controls ($\mathbf{X}_{bft}$) are log-firm default probability, log-outstanding credit, and log-collateral. Firm-level controls ($\mathbf{X}_{f0(b)}$) are total number of lenders, firm age deciles, log-assets, cash/assets, intangibles/assets, net working capital/assets, equity/liabilities, retained earnings/assets, EBIT/assets, sales/assets, all measured at the beginning of the relationship. Specifications include bank-by-time and bank-by-firm fixed effects. Estimation sample is a quarterly panel of bank-firm relationships from the Belgian Corporate Credit Register (CCR) over the period 2012 Q2 to 2021 Q4 using

Table 7: Specialized Banks Match With Riskier Firms

Outcome	$\mathbb{1}\{\text{Rel. start}_{bft}\}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Firm characteristic (x_{ft-1})	Z-score	Equity/L	Cash/A	NWC/A	Intang/A	EBIT/A	Retained/A
x_{ft-1}	0.0002	-0.01***	-0.01***	-0.009***	-0.02***	-0.005***	-0.007***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
$\text{Spe}_{bs(f)t}$	1.2***	1.2***	1.2***	1.2***	1.4***	1.2***	1.2***
	(0.03)	(0.02)	(0.02)	(0.02)	(0.08)	(0.02)	(0.02)
$x_{ft-1} \times \text{Spe}_{bs(f)t}$	-0.08***	-0.09***	-0.09***	-0.06***	0.06***	-0.05***	-0.03**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Bank-Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NACE-2D-Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,305,267	6,168,829	6,468,716	6,350,588	649,499	6,157,465	6,275,576
Adjusted R^2	0.16	0.16	0.16	0.16	0.14	0.16	0.16

Notes: Table reports estimated coefficients of interest from:

$$\mathbb{1}\{\text{Rel. start}_{bft}\} = \alpha + \beta_0 \cdot x_{ft-4} + \beta_1 \cdot \text{Spe}_{bs(f)t} + \beta_2 \cdot x_{ft-4} \times \text{Spe}_{bs(f)t} + \eta_{bt} + \eta_{s(f)t} + \eta_{p(f)t} + \varepsilon_{bft},$$

where $\mathbb{1}\{\text{Rel. start}_{bft}\}$ is an indicator variable equal to one if firm f matches with bank b, and x_{ft-1} is either the firm's Altman Z-score (column 1), equity/liabilities (column 2), cash/assets (column 3), net working capital/assets (column 4), intangibles/assets (column 5), return on assets (column 6), and retained earnings/assets (column 7), all lagged one year. $Spe_{bs(f)t}$ is a measure of excess bank specialization in sector s defined in Section 2.3 Specialization is centered and scaled by the average top sector specialization across banks. Specifications include bank-by-time and bank-by-firm fixed effects. Estimation sample contains new matches between banks and firms from the Belgian Corporate Credit Register (CCR) over the period 2012 Q2 to 2021 Q4 using term loans and credit lines (cf. Appendix A.2). Any lender that formed new relationships in an industry that quarter is considered as an alternative. Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 8: Risky Firms Have Longer Relationships With Specialized banks

Outcome	Overall RL_{bf} (1)
$\ln(PD_{bft})$	-0.22***
	(0.008)
$\text{Spe}_{bs(f)t}$	0.38***
	(0.09)
$\ln(PD_{bft}) \times \text{Spe}_{bs(f)t}$	0.19***
	(0.03)
Relationship controls	Yes
Firm controls	Yes
NACE-2D-Time FEs	Yes
Province-Time FEs	Yes
Bank-Time FEs	Yes
Observations	125,957
Adjusted R^2	0.40

Notes: Table reports estimated coefficients of interest from:

$$\text{Overall RL}_{bf} = \alpha + \beta_0 \cdot \ln(PD_{bfT}) + \beta_1 \cdot \text{Spe}_{bs(f)0} + \beta_2 \cdot \ln(PD_{bfT}) \times \text{Spe}_{bs(f)0}$$
$$+ \beta_3 \cdot \mathbf{X}_{bfT} + \beta_4 \cdot \mathbf{X}_{f0(b)} + \eta_{bT} + \eta_{s(f)T} + \eta_{p(f)T} + \varepsilon_{bf},$$

where Overall RL_{bf} is the overall relationship length in years between bank b and firm f, PD_{bfT} is the firm default probability at the end of the relationship, and $Spe_{bs(f)0}$ is a measure of excess bank specialization in sector s at the start of the relationship, defined in Section 2.3. Specialization is centered and scaled by the average top sector specialization across banks. Relationship controls ($\mathbf{X}_{bfT}$) are log-authorized and log-maturity credit at the time of separation Firm-level controls ($\mathbf{X}_{f0(b)}$) are total number of lenders, firm age deciles, log-assets, cash/assets, intangibles/assets, net working capital/assets, equity/liabilities, retained earnings/assets, EBIT/assets, sales/assets, all measured at the beginning of the relationship. Specification includes bank-by-time and bank-by-firm fixed effects. Sample of credit relationships with observed end date not resulting from the firm being in default. Obtained from the Belgian Corporate Credit Register (CCR) over the period 2012 Q2 to 2021 Q4 using terms loans only and credit lines (cf. Appendix A.2). Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 9: Firms Benefit from Relationships with Specialized Lenders

Outcome	Δ(Eearnings/A) (1)	Δ(Retained/A) (2)	Δ log(Cash) (3)	Δ(Equity/A) (4)	Δ(NWC/A) (5)	Δ(Trade cre/A) (6)
RL_{bft}	0.22***	0.12***	20.1***	24.2***	13.7***	2.1***
	(0.05)	(0.02)	(0.48)	(0.29)	(0.22)	(0.06)
$\text{Spe}_{bs(f)t}$	-0.26	-0.29*	-9.9***	-0.92	-3.2**	-1.0**
	(0.34)	(0.17)	(3.2)	(1.7)	(1.4)	(0.44)
$RL_{bft} \times \text{Spe}_{bs(f)t}$	0.59***	0.31***	5.7***	3.3***	4.3***	1.1***
	(0.18)	(0.09)	(2.0)	(1.2)	(0.93)	(0.36)
Relationship controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
NACE-2D-Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Province-Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,562,301	1,533,723	1,369,159	1,367,389	1,364,907	1,352,441
Adjusted R^2	0.06	0.03	0.06	0.11	0.09	0.04

Notes: Table reports estimated coefficients of interest from:

$$\Delta y_{ft,0(b)} = \alpha + \beta_0 \cdot RL_{bft} + \beta_1 \cdot \text{Spe}_{bs(f)t} + \beta_2 \cdot RL_{bft} \times \text{Spe}_{bs(f)t} + \beta_3 \cdot \mathbf{X}_{bft} + \beta_4 \cdot \mathbf{X}_{f0(b)} + \eta_{bt} + \eta_{s(f)t} + \eta_{p(f)t} + \varepsilon_{bft},$$

where $\Delta y_{bft0(b)}$ is a measure of firm outcome growth since the start of its relationship with bank b, i.e., change in earnings/assets (column 1), change in retained earnings/assets (column 2), cash reserved growth (column 3), change in equity/assets (column 4), change in net working capital/assets (column 5), change in net trade credit/assets (column 6). RL_{bft} is the relationship length between firm f and bank b, PD_{bft} is firm f's default probability assessed by bank b, and $Spe_{bs(f)t}$ is a measure of excess bank specialization in sector s defined in Section 2.3. Specialization is centered and scaled by the average top sector specialization across banks and RL_{bft} is scaled by its standard deviation. Relationship controls ($\mathbf{X}_{bft}$) are log-firm default probability, log-outstanding credit, and log-collateral. Firm-level controls ($\mathbf{X}_{f0(b)}$) are total number of lenders, firm age deciles, log-assets, cash/assets, intangibles/assets, net working capital/assets, equity/liabilities, retained earnings/assets, EBIT/assets, sales/assets, all measured at the beginning of the relationship. Specifications include bank-by-time and bank-by-firm fixed effects. Estimation sample is an annual panel of bank-firm relationships from the Belgian Corporate Credit Register (CCR) over the period 2012-2021 using term loans and credit lines (cf. Appendix A.2). Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 10: Specialized-Financed Firms Are More Productive

Outcome	Δ(EBIT/A) (1)	$\Delta \log$(Sales/A) (2)	$\Delta \log$(CapEx) (3)	$\Delta \log$(Inputs) (4)	$\Delta \log$(Materials) (5)	$\Delta \log$(Wages) (6)
RL_{bft}	-0.33***	-4.9***	-39.5***	8.1***	0.12	11.7***
	(0.06)	(0.19)	(1.3)	(0.26)	(0.62)	(0.76)
$\text{Spe}_{bs(f)t}$	-0.68	-3.5**	-10.0	-3.3*	-8.4**	-3.4
	(0.43)	(1.4)	(11.0)	(1.7)	(3.8)	(4.9)
$RL_{bft} \times \text{Spe}_{bs(f)t}$	0.93***	1.9**	22.9***	2.7**	6.5***	1.4
	(0.23)	(0.82)	(5.7)	(1.1)	(2.4)	(3.4)
Relationship controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
NACE-2D-Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Province-Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,560,369	1,352,283	970,134	1,374,409	1,365,137	1,573,985
Adjusted R^2	0.06	0.05	0.04	0.05	0.01	0.02

Notes: Table reports estimated coefficients of interest from:

$$\Delta y_{ft,0(b)} = \alpha + \beta_0 \cdot RL_{bft} + \beta_1 \cdot \text{Spe}_{bs(f)t} + \beta_2 \cdot RL_{bft} \times \text{Spe}_{bs(f)t} + \beta_3 \cdot \mathbf{X}_{bft} + \beta_4 \cdot \mathbf{X}_{f0(b)} + \eta_{bt} + \eta_{s(f)t} + \eta_{p(f)t} + \varepsilon_{bft},$$

where $\Delta y_{bft0(b)}$ is a measure of firm outcome growth since the start of its relationship with bank b, i.e., change in EBIT/assets (column 1), sales/assets growth (column 2), CapEx growth (column 3), inputs expenditure growth (column 4), materials expenditure growth (column 5), payroll growth (column 6). RL_{bft} is the relationship length between firm f and bank b, PD_{bft} is firm f's default probability assessed by bank b, and $Spe_{bs(f)t}$ is a measure of excess bank specialization in sector s defined in Section 2.3. Specialization is centered and scaled by the average top sector specialization across banks and RL_{bft} is scaled by its standard deviation. Relationship controls ($\mathbf{X}_{bft}$) are log-firm default probability, log-outstanding credit, and log-collateral. Firm-level controls ($\mathbf{X}_{f0(b)}$) are total number of lenders, firm age deciles, log-assets, cash/assets, intangibles/assets, net working capital/assets, equity/liabilities, retained earnings/assets, EBIT/assets, sales/assets, all measured at the beginning of the relationship. Specifications include bank-by-time and bank-by-firm fixed effects. Estimation sample is an annual panel of bank-firm relationships from the Belgian Corporate Credit Register (CCR) over the period 2012-2021 using term loans and credit lines (cf. Appendix A.2). Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

References

Acharya, Viral V., Iftekhar Hasan, and Anthony Saunders. 2006. "Should Banks Be Diversified? Evidence from Individual Bank Loan Portfolios." *The Journal of Business*, 79(3): 1355–1412.

Agarwal, Sumit, and Robert Hauswald. 2010. "Distance and Private Information in Lending." *The Review of Financial Studies*, 23(7): 2757–2788.

Amiti, Mary, and David E. Weinstein. 2018. "How Much Do Idiosyncratic Bank Shocks Affect Investment? Evidence from Matched Bank-Firm Loan Data." *Journal of Political Economy*, 126(2): 525–587.

Banerjee, Abhijit V., and Esther Duflo. 2014. "Do Firms Want to Borrow More? Testing Credit Constraints Using a Directed Lending Program." *The Review of Economic Studies*, 81(2 (287)): 572–607.

Banerjee, Ryan N., Leonardo Gambacorta, and Enrico Sette. 2021. "The Real Effects of Relationship Lending." *Journal of Financial Intermediation*, 48: 100923.

Beck, Thorsten, Asli Demirgüc-Kunt, and Vojislav Maksimovic. 2005. "Financial and Legal Constraints to Growth: Does Firm Size Matter?" *The Journal of Finance*, 60(1): 137–177.

Berger, Allen N., and Gregory F. Udell. 1995. "Relationship Lending and Lines of Credit in Small Firm Finance." *The Journal of Business*, 68(3): 351–381.

Berger, Allen N, and Gregory F Udell. 1998. "The Economics of Small Business Finance: The Roles of Private Equity and Debt Markets in the Financial Growth Cycle." *Journal of Banking & Finance*, 22(6): 613–673.

Berger, Allen N., Nathan H. Miller, Mitchell A. Petersen, Raghuram G. Rajan, and Jeremy C. Stein. 2005. "Does Function Follow Organizational Form? Evidence from the Lending Practices of Large and Small Banks." *Journal of Financial Economics*, 76(2): 237–269.

Berger, Philip G., Michael Minnis, and Andrew Sutherland. 2017. "Commercial Lending Concentration and Bank Expertise: Evidence from Borrower Financial Statements." *Journal of Accounting and Economics*, 64(2): 253–277.

Bharath, Sreedhar T., Sandeep Dahiya, Anthony Saunders, and Anand Srinivasan. 2011. "Lending Relationships and Loan Contract Terms." *The Review of Financial Studies*, 24(4): 1141–1203.

Black, Sandra E., and Philip E. Strahan. 2002. "Entrepreneurship and Bank Credit Availability." *The Journal of Finance*, 57(6): 2807–2833.

Blickle, Kristian. 2022. "Local Banks, Credit Supply, and House Prices." *Journal of Financial Economics*, 143(2): 876–896.

Blickle, Kristian, Cecilia Parlatore, and Anthony Saunders. 2024. "Specialization in Banking." National Bureau of Economic Research Working Paper 31077.

Blickle, Kristian, Zhiguo He, Jing Huang, and Cecilia Parlatore. 2024. "Information-Based Pricing in Specialized Lending." National Bureau of Economic Research Working Paper 32155.

Bolton, Patrick, Xavier Freixas, Leonardo Gambacorta, and Paolo Emilio Mistrulli. 2016. "Relationship and Transaction Lending in a Crisis." *The Review of Financial Studies*, 29(10): 2643–2676.

Bonfim, Diana, Ralph De Haas, Alexandra Matyunina, and Steven Ongena. 2024. "Bank Specialization in Lending to New Firms." European Central Bank Working Paper.

Boot, Arnoud W. A., and Anjan V. Thakor. 1994. "Moral Hazard and Secured Lending in an Infinitely Repeated Credit Market Game." *International Economic Review*, 35(4): 899–920.

Boot, Arnoud W. A., and Anjan V. Thakor. 2000. "Can Relationship Banking Survive Competition?" *The Journal of Finance*, 55(2): 679–713.

Boyd, John H, and Edward C Prescott. 1986. "Financial Intermediary-Coalitions." *Journal of Economic Theory*, 38(2): 211–232.

Carey, Mark, Mitch Post, and Steven A. Sharpe. 1998. "Does Corporate Lending by Banks and Finance Companies Differ? Evidence on Specialization in Private Debt Contracting." *The Journal of Finance*, 53(3): 845–878.

Cetorelli, Nicola, and Philip E. Strahan. 2006. "Finance as a Barrier to Entry: Bank Competition and Industry Structure in Local U.S. Markets." *The Journal of Finance*, 61(1): 437–461.

Chen, Jiawei, and Kejun Song. 2013. "Two-Sided Matching in the Loan Market." *International Journal of Industrial Organization*, 31(2): 145–152.

Cotugno, Matteo, Stefano Monferrà, and Gabriele Sampagnaro. 2013. "Relationship Lending, Hierarchical Distance and Credit Tightening: Evidence from the Financial Crisis." *Journal of Banking & Finance*, 37(5): 1372–1385.

Crawford, Gregory S., Nicola Pavanini, and Fabiano Schivardi. 2018. "Asymmetric Information and Imperfect Competition in Lending Markets." *American Economic Review*, 108(7): 1659–1701.

Degryse, Hans, and Steven Ongena. 2005. "Distance, Lending Relationships, and Competition." *The Journal of Finance*, 60(1): 231–266.

Degryse, Hans, Olivier De Jonghe, Leonardo Gambacorta, and Cédric Huylebroek. 2024. "Bank Specialisation and Corporate Innovation." BIS Working Paper 1218.

De Haas, Ralph, and Neeltje Van Horen. 2012. “International Shock Transmission after the Lehman Brothers Collapse: Evidence from Syndicated Lending.” *American Economic Review*, 102(3): 231–37.

De Jonghe, Olivier, Hans Dewachter, and Steven Ongena. 2020. “Bank Capital (Requirements) and Credit Supply: Evidence from Pillar 2 Decisions.” *Journal of Corporate Finance*, 60: 101518.

Deyoung, Robert, Anne Gron, Gökhan Torna, and Andrew Winton. 2015. “Risk Overhang and Loan Portfolio Decisions: Small Business Loan Supply before and during the Financial Crisis.” *The Journal of Finance*, 70(6): 2451–2488.

Diamond, Douglas W. 1984. “Financial Intermediation and Delegated Monitoring.” *The Review of Economic Studies*, 51(3): 393–414.

Duquerroy, Anne, Clément Mazet-Sonilhac, Jean-Stéphane Mésonnier, and Daniel Paravisini. 2022. “Bank Local Specialization.” Banque de France SSRN Scholarly Paper 4034634, Rochester, NY.

Fazzari, Steven M., R. Glenn Hubbard, Bruce C. Petersen, Alan S. Blinder, and James M. Poterba. 1988. “Financing Constraints and Corporate Investment.” *Brookings Papers on Economic Activity*, 1988(1): 141–206.

Gelman, Michael, Itay Goldstein, and Andrew MacKinlay. 2023. “Bank Diversification and Lending Resiliency.” University of Pennsylvania SSRN Scholarly Paper 4147790, Rochester, NY.

Gertler, Mark, and Simon Gilchrist. 1994. “Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms*.” *The Quarterly Journal of Economics*, 109(2): 309–340.

Giannetti, Mariassunta, and Farzad Saidi. 2019. “Shock Propagation and Banking Structure.” *The Review of Financial Studies*, 32(7): 2499–2540.

Giometti, Marco, and Stefano Pietrosanti. 2022. “Bank Specialization and the Design of Loan Contracts.” CFR SSRN Scholarly Paper 4470135, Rochester, NY.

Gopal, Manasa, and Philipp Schnabl. 2022. “The Rise of Finance Companies and FinTech Lenders in Small Business Lending.” *The Review of Financial Studies*, 35(11): 4859–4901.

Granja, João, Gregor Matvos, and Amit Seru. 2017. “Selling Failed Banks.” *The Journal of Finance*, 72(4): 1723–1784.

Ioannidou, Vasso, and Steven Ongena. 2010. ““Time for a Change”: Loan Conditions and Bank Behavior When Firms Switch Banks.” *The Journal of Finance*, 65(5): 1847–1877.

Jahn, Nadya, Christoph Memmel, and Andreas Pfingsten. 2016. “Banks’ Specialization versus Diversification in the Loan Portfolio.” *Schmalenbach Business Review*, 17(1): 25–48.

James, Christopher. 1987. "Some Evidence on the Uniqueness of Bank Loans." *Journal of Financial Economics*, 19(2): 217–235.

Jiang, Shuyi, and Jay Y. Li. 2022. "He Who Lends Knows." *Journal of Banking & Finance*, 138: 106412.

Karolyi, Stephen Adam. 2018. "Personal Lending Relationships." *The Journal of Finance*, 73(1): 5–49.

Khwaja, Asim Ijaz, and Atif Mian. 2008. "Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market." *American Economic Review*, 98(4): 1413–1442.

Kosekova, Kamelia, Angela Maddaloni, Melina Papoutsi, and Fabiano Schivardi. 2023. "Firm-Bank Relationships: A Cross-Country Comparison." European Central Bank SSRN Scholarly Paper, Rochester, NY.

Lummer, Scott L., and John J. McConnell. 1989. "Further Evidence on the Bank Lending Process and the Capital-Market Response to Bank Loan Agreements." *Journal of Financial Economics*, 25(1): 99–122.

Mian, Atif. 2006. "Distance Constraints: The Limits of Foreign Lending in Poor Economies." *The Journal of Finance*, 61(3): 1465–1505.

Papoutsi, Melina. 2024. "Lending Relationships in Loan Renegotiation: Evidence from Corporate Loans." European Central Bank SSRN Scholarly Paper, Rochester, NY.

Paravisini, Daniel, Veronica Rappoport, and Philipp Schnabl. 2023. "Specialization in Bank Lending: Evidence from Exporting Firms." *The Journal of Finance*, 78(4): 2049–2085.

Petersen, Mitchell A., and Raghuram G. Rajan. 1994. "The Benefits of Lending Relationships: Evidence from Small Business Data." *The Journal of Finance*, 49(1): 3–37.

Petersen, Mitchell A., and Raghuram G. Rajan. 1995. "The Effect of Credit Market Competition on Lending Relationships." *The Quarterly Journal of Economics*, 110(2): 407–443.

Rajan, Raghuram G. 1992. "Insiders and Outsiders: The Choice between Informed and Arm's-Length Debt." *The Journal of Finance*, 47(4): 1367–1400.

Santos, João a. C., and Andrew Winton. 2008. "Bank Loans, Bonds, and Information Monopolies across the Business Cycle." *The Journal of Finance*, 63(3): 1315–1359.

Schwert, Michael. 2018. "Bank Capital and Lending Relationships." *The Journal of Finance*, 73(2): 787–830.

Sette, Enrico, and Giorgio Gobbi. 2015. "Relationship Lending During a Financial Crisis." *Journal of the European Economic Association*, 13(3): 453–481.

Sharpe, Steven A. 1990. "Asymmetric Information, Bank Lending, and Implicit Contracts: A Stylized Model of Customer Relationships." *The Journal of Finance*, 45(4): 1069–1087.

Stein, Jeremy C. 2002. "Information Production and Capital Allocation: Decentralized versus Hierarchical Firms." *The Journal of Finance*, 57(5): 1891–1921.

Stiglitz, Joseph E., and Andrew Weiss. 1981. "Credit Rationing in Markets with Imperfect Information." *The American Economic Review*, 71(3): 393–410.

Tielens, Joris, Christophe Piette, and Olivier De Jonghe. 2020. "Belgian Corporate Sector Liquidity and Solvency in the COVID-19 Crisis : A Post-First-Wave Assessment." *NBB Economic Review*.

Uchida, Hirofumi, Gregory F. Udell, and Nobuyoshi Yamori. 2012. "Loan Officers and Relationship Lending to SMEs." *Journal of Financial Intermediation*, 21(1): 97–122.

von Thadden, Ernst-Ludwig. 2004. "Asymmetric Information, Bank Lending and Implicit Contracts: The Winner's Curse." *Finance Research Letters*, 1(1): 11–23.

Whited, Toni M., Yufeng Wu, and Kairong Xiao. 2021. "Low Interest Rates and Risk Incentives for Banks with Market Power." *Journal of Monetary Economics*, 121: 155–174.

Winton, Andrew. 1999. "Don't Put All Your Eggs in One Basket? Diversification and Specialization in Lending." University of Minnesota SSRN Scholarly Paper 173615, Rochester, NY.

Appendix

A Additional Data Description

A.1 Data Cleaning

A.2 Sample Selection

BECRIS sample selection. We keep unconsolidated banks with Belgian activity subject to regulatory filings at the NBB (Schema A). We keep banks in quarters where they have at least one hundred borrowers. Some institutions might be conglomerate banks providing financing to other entities within the group and do not face the same constraints and incentives as other credit institutions. We keep only Belgian firms and drop financial institutions, public sector firms, educational firms, government entities, and nonprofit organizations. While both limited and unlimited liability firms are present (e.g., sole proprietorships, partnerships), only limited liability entities report annual accounts. We keep only term loans regardless of their contract characteristics (loan purpose, interest type, repayment rights). We keep contracts with positive interest rates and maturities. When a contract has an authorized amount of zero, we assign the maximum used amount as long as the contract did not go into forbearance. We assign as missing any default probability below 0.03% in accordance to AnaCredit regulations.

B Derivation of the Switching Threshold to a New Relationship

In specification (**??**), we standardize our variables of interest for ease of interpretation and define

$$\widetilde{\text{Spe}}_{bs(f)} := \frac{\text{Spe}_{bs(f)} - \mu\Big(\text{Spe}_{bs(f)}\Big)}{\mu^{\text{top}}\Big(\text{Spe}_{bs(f)}\Big)}$$

$$\widetilde{RL}_{bf} := \frac{RL_{bf}}{\sigma(RL_{bf})},$$

where $\mu(\text{Spe}_{bs(f)})$ and $\sigma(RL_{bf})$ to denote the mean and standard deviation of lender industry specialization and relationship length respectively in the estimation sample, and $\mu^{\text{top}}(\text{Spe}_{bs(f)})$ designates the average specialization across all banks' top industry of specialization. Holding all other covariates to their mean and omitting them from the relationship, the predicted interest rate after estimation is

$$\widehat{R}_{bfc} = \widehat{\beta}_1 \cdot \widetilde{RL}_{bf} + \widehat{\beta}_2 \cdot \widetilde{\text{Spe}}_{bs(f)} + \widehat{\beta}_3 \cdot \widetilde{RL}_{bf} \times \widetilde{\text{Spe}}_{bs(f)}.$$

The relationship length threshold such that the average firm belonging to a bank's most preferred industry would face a lower rate by starting a new relationship with a diversified lender satisfies

$$\begin{aligned}
& \widehat{R}_{bfc}\Big(RL_{bf} = 0 \cap \text{Spe}_{bs(f)} = 0\Big) = \widehat{R}_{bfc}\Big(\text{Spe}_{bs(f)} = \mu^{\text{top}}\Big(\text{Spe}_{bs(f)}\Big)\Big) \\
\Leftrightarrow \quad & -\widehat{\beta}_2 \cdot \frac{\mu\Big(\text{Spe}_{bs(f)}\Big)}{\mu^{\text{top}}\Big(\text{Spe}_{bs(f)}\Big)} = \widehat{\beta}_1 \cdot \frac{RL_{bf}}{\sigma(RL_{bf})} + \widehat{\beta}_2 \cdot \left(1 - \frac{\mu\Big(\text{Spe}_{bs(f)}\Big)}{\mu^{\text{top}}\Big(\text{Spe}_{bs(f)}\Big)}\right) \\
& \qquad + \widehat{\beta}_3 \cdot \frac{RL_{bf}}{\sigma(RL_{bf})} \times \left(1 - \frac{\mu\Big(\text{Spe}_{bs(f)}\Big)}{\mu^{\text{top}}\Big(\text{Spe}_{bs(f)}\Big)}\right) \\
\Leftrightarrow \quad & \widehat{\beta}_1 \cdot \frac{RL_{bf}}{\sigma(RL_{bf})} + \widehat{\beta}_2 + \widehat{\beta}_3 \cdot \frac{RL_{bf}}{\sigma(RL_{bf})} \times \left(1 - \frac{\mu\Big(\text{Spe}_{bs(f)}\Big)}{\mu^{\text{top}}\Big(\text{Spe}_{bs(f)}\Big)}\right) = 0 \\
\Leftrightarrow \quad & RL_{bf} = \frac{-\widehat{\beta}_2}{\widehat{\beta}_1 + \widehat{\beta}_3\left(1 - \frac{\mu\left(\text{Spe}_{bs(f)}\right)}{\mu^{\text{top}}\left(\text{Spe}_{bs(f)}\right)}\right)} \sigma(RL_{bf}).
\end{aligned}$$

In the data, $\mu\Big(\text{Spe}_{bs(f)}\Big) \approx 0.145$, $\mu^{\text{top}}(\text{Spe}_{bs(f)}) \approx 0.004$, and $\sigma(RL_{bf}) \approx 6.4$.

C Supplementary Tables and Figures

Table C.1: Summary Statistics of Firms in the CCR

	Mean	SD	Pctl 10	Med	Pctl 90	Pctl 99
Panel A: balance sheet						
Assets (K€)	5.30	342.20	0.10	0.40	3.00	34.20
Cash in hand (K€)	0.30	18.40	0.00	0.00	0.30	2.80
NWC / assets (%)	-789.90	291838.40	-37.60	11.80	61.70	91.50
Intangibles / assets (%)	1.90	8.40	0.00	0.00	1.70	49.40
Equity / liabilities (%)	576.90	79018.00	-7.90	44.40	312.70	2534.30
Altman Z-score	1.70	739.90	-0.10	0.90	2.90	11.10
Firm age (years)	15.40	11.70	3.20	12.70	30.60	52.00
Panel B: income statement						
Sales (K€)	0.50	19.70	0.00	0.00	0.40	4.90
Employees (FTE)	5.00	103.20	0.00	0.00	6.00	55.00
EBIT (K€)	0.10	5.60	-0.00	0.00	0.20	1.60
CapEx (K€)	0.00	1.60	0.00	0.00	0.00	0.20
Retained / assets (%)	-76.30	98376.30	0.00	0.00	9.40	32.80
Inputs / assets (%)	83.80	37967.30	0.80	14.30	62.00	189.20
Materials / assets (%)	50.40	23989.40	0.00	4.30	44.20	154.30
Payroll / assets (%)	6.60	1778.00	0.00	0.00	11.40	41.50
Panel C: relationship with lender						
N lenders	1.20	0.50	1.00	1.00	2.00	3.00
Rel. length (years)	5.90	4.90	0.70	4.60	13.30	19.20
Credit outstanding (K€)	0.20	3.00	0.00	0.00	0.30	2.70
Collateral amount (K€)	0.50	8.20	0.00	0.00	0.80	6.40
Default probability (%)	6.90	20.60	0.10	0.80	9.90	100.00

Notes: Table reports summary statistics between 2012 Q2 to 2021 Q4 for the sample of firms used in Section 4. See Appendix A.1 for variables construction. Quarterly credit data sourced from the Belgian Corporate Credit Register (cf. Appendix A.2); annual firm balance sheets and income statements from the Annual Accounts; sales, capital expenditure, and inputs data from firms VAT declarations; employment data from firms social security declarations.

Table C.2: Invest-Harvest Behavior (Maturity): Robustness to Fixed Effects

Outcome	Matur_{bfct}				
	(1)	(2)	(3)	(4)	(5)
RL_{bft}	-0.23***	-0.07***	-0.06***	-0.06***	-3.2***
	(0.007)	(0.007)	(0.006)	(0.006)	(0.50)
$\text{Spe}_{bs(f)t}$	0.38***	-0.05	-0.18***	-0.42***	-0.37***
	(0.05)	(0.06)	(0.06)	(0.06)	(0.13)
$RL_{bft} \times \text{Spe}_{bs(f)t}$	0.37***	0.17***	0.16***	0.21***	0.11*
	(0.05)	(0.04)	(0.04)	(0.04)	(0.07)
Firm controls		Yes	Yes	Yes	Yes
Contract controls		Yes	Yes	Yes	Yes
Relationship controls		Yes	Yes	Yes	Yes
Bank-time FEs			Yes	Yes	Yes
(NACE & Prov)-time FEs				Yes	
Bank-firm FEs					Yes
Observations	703,077	502,304	502,298	502,234	441,863
Adjusted R^2	0.007	0.47	0.49	0.49	0.65

Notes: Table reports estimated coefficients of interest from:

$$\text{Matur}_{bfct} = \alpha + \beta_0 \cdot RL_{bft} + \beta_1 \cdot \text{Spe}_{bs(f)t} + \beta_2 \cdot RL_{bft} \times \text{Spe}_{bs(f)t} + \beta_3 \cdot \mathbf{X}_{bfct} + \beta_4 \cdot \mathbf{X}_{bft} + \beta_5 \cdot \mathbf{X}_{ft-4} + \eta_{bc} + \eta_{bt} + \eta_{bf} + \varepsilon_{bfct},$$

where $Matur_{bfct}$ is the maturity in years of contract c between bank b to firm f at time t, RL_{bft} is the relationship length between firm f and bank b, $Spe_{bs(f)t}$ is a measure of excess bank specialization in sector s defined in Section 2.3, and PD_{bft} is firm f's default probability assessed by bank b. Specialization is centered and scaled by the average top sector specialization across banks and RL_{bft} is scaled by its standard deviation. Contract controls ($\mathbf{X}_{bfct}$) are log-authorized credit and contract maturity. Relationship controls ($\mathbf{X}_{bft}$) are default probability deciles, log-outstanding credit, and the number of outstanding contracts. Firm-level controls ($\mathbf{X}_{ft-4}$) are total number of lenders, log-assets, cash/assets, intangibles/assets, net working capital/assets, equity/liabilities, retained earnings/assets, EBIT/assets, sales/assets, all lagged one year, and firm age deciles. Bank-contract-level fixed effects (η_{bc}) are interest rate type, instrument purpose, instrument repayment rights, origination vs. renegotiation indicator, and a collateralized indicator, all interacted with bank fixed effects (cf. Appendix A.1). Quarterly contract-level estimation sample uses credit lines and term loans at origination and renegotiation from IRB banks between 2018 Q4 and 2023 Q4. Sourced from BECRIS, Belgium's AnaCredit (cf. Appendix A.2). Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table C.3: Invest-Harvest Behavior (Maturity): Robustness to Measures of Specialization

Outcome	Matur_{bfct}			
	(1)	(2)	(3)	(4)
Sample	Drop 99th	Relative	-log(Rank)	Geo. spe.
RL_{bft}	-3.2***	-3.2***	-3.2***	-3.2***
	(0.50)	(0.50)	(0.50)	(0.50)
$\text{Spe}_{bs(f)t}$	-0.19***	-0.24	-0.03***	-0.36***
	(0.07)	(0.74)	(0.009)	(0.13)
$\text{Geo spe}_{bp(f)t}$				-0.01
				(0.13)
$RL_{bft} \times \text{Spe}_{bs(f)t}$	0.06*	-0.21	0.010*	0.11*
	(0.04)	(0.39)	(0.005)	(0.07)
$RL_{bft} \times \text{Geo spe}_{bp(f)t}$				0.002
				(0.08)
Contract controls	Yes	Yes	Yes	Yes
Relationship controls	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Bank-time FEs	Yes	Yes	Yes	Yes
Bank-firm FEs	Yes	Yes	Yes	Yes
Observations	441,823	441,863	441,863	441,863
Adjusted R^2	0.65	0.65	0.65	0.65

Notes: Table reports estimated coefficients of interest from specification (1), where $Matur_{bfct}$ is the maturity in years of contract c between bank b to firm f at time t, RL_{bft} is the relationship length between firm f and bank b. RL_{bft} is scaled by its standard deviation. $Spe_{bs(f)t}$ refers to various measures of bank industry specialization. Column (1) drops the top 99th percentile of excess specialization ($\frac{L_{bs}}{L_b} - \frac{L_s}{L}$), column (2) uses relative specialization ($\frac{L_{bs}}{L_b} / \frac{L_s}{L}$), column (3) uses (minus) the log-rank of each industry sorted by decreasing order of specialization in their portfolio ($\text{Rank}(Spe_{bs} \mid s \in \mathcal{S}_b)$), and column (4) uses both excess industry specialization and bank excess geographical specialization in province p ($Spe_{bp} = \frac{L_{bp}}{L_b} - \frac{L_p}{L}$). In all columns but (3), specialization measures are centered and scaled by the average top sector specialization across banks. Contract controls ($\mathbf{X}_{bfct}$) are interest rate and log-authorized credit. Relationship controls ($\mathbf{X}_{bft}$) are default probability deciles, log-outstanding credit, and the number of outstanding contracts. Firm-level controls ($\mathbf{X}_{ft-4}$) are total number of lenders, log-assets, cash/assets, intangibles/assets, net working capital/assets, equity/liabilities, retained earnings/assets, EBIT/assets, sales/assets, all lagged one year, and firm age deciles. Bank-contract-level fixed effects (η_{bc}) are interest rate type, instrument purpose, instrument repayment rights, origination vs. renegotiation indicator, and a collateralized indicator, all interacted with bank fixed effects (cf. Appendix A.1). Quarterly contract-level estimation sample uses credit lines and term loans at origination and renegotiation from IRB banks between 2018 Q4 and 2023 Q4. Sourced from BECRIS, Belgium's AnaCredit (cf. Appendix A.2). Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table C.4: Invest-Harvest Behavior: Drop COVID Moratorium

Outcome	R_{bfct}	
	(1)	(2)
Sample	Drop moratorium contracts	Drop moratorium period
RL_{bft}	29.0*	38.8*
	(17.1)	(20.3)
$\text{Spe}_{bs(f)t}$	-25.3***	-15.9***
	(6.4)	(5.3)
$RL_{bft} \times \text{Spe}_{bs(f)t}$	8.8***	6.4*
	(3.0)	(3.5)
Contract controls	Yes	Yes
Relationship controls	Yes	Yes
Firm controls	Yes	Yes
Bank-time FEs	Yes	Yes
Bank-firm FEs	Yes	Yes
Observations	425,134	305,029
Adjusted R^2	0.78	0.80

Notes: Table reports estimated coefficients of interest from:

$$\begin{aligned} R_{bfct} &= \alpha + \beta_0 \cdot RL_{bft} + \beta_1 \cdot \text{Spe}_{bs(f)t} + \beta_2 \cdot RL_{bft} \times \text{Spe}_{bs(f)t} \\ &+ \beta_3 \cdot \mathbf{X}_{bfct} + \beta_4 \cdot \mathbf{X}_{bft} + \beta_5 \cdot \mathbf{X}_{ft-4} + \eta_{bc} + \eta_{bt} + \eta_{bf} + \varepsilon_{bfct}, \end{aligned}$$

where contracts subject to the debt moratorium enforced by the Belgian government and the entire moratorium period (April 2020-June 2021) are dropped from the estimation sample in columns (1) and (2), respectively. R_{bfct} is the interest rate in basis points charged by bank b to firm f for credit contract c at time t, RL_{bft} is the relationship length between firm f and bank b, and $Spe_{bs(f)t}$ is a measure of excess bank specialization in sector s defined in Section 2.3. Specialization is centered and scaled by the average top sector specialization across banks and RL_{bft} is scaled by its standard deviation. Contract controls ($\mathbf{X}_{bfct}$) are log-authorized credit and contract maturity. Relationship controls ($\mathbf{X}_{bft}$) are default probability deciles, log-outstanding credit, and the number of outstanding contracts. Firm-level controls ($\mathbf{X}_{ft-4}$) are total number of lenders, log-assets, cash/assets, intangibles/assets, net working capital/assets, equity/liabilities, retained earnings/assets, EBIT/assets, sales/assets, all lagged one year, and firm age deciles. Bank-contract-level fixed effects (η_{bc}) are interest rate type, instrument purpose, instrument repayment rights, origination vs. renegotiation indicator, and a collateralized indicator, all interacted with bank fixed effects (cf. Appendix A.1). Quarterly contract-level estimation sample uses credit lines and term loans at origination and renegotiation from IRB banks between 2018 Q4 and 2023 Q4. Sourced from BECRIS, Belgium's AnaCredit (cf. Appendix A.2). Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table C.5: Invest-Harvest Behavior of Specialized Banks in the CCR Data

Outcome	$\widetilde{R}_{ft}$	
	(1)	(2)
$\ln(PD_{bft})$	77.5***	85.2***
	(1.8)	(2.9)
RL_{bft}	113.1***	111.8***
	(3.0)	(3.1)
$\text{Spe}_{bs(f)t}$	-38.2	-50.4
	(34.0)	(35.1)
$\ln(PD_{bft}) \times \text{Spe}_{bs(f)t}$		-47.2**
		(19.3)
$\ln(PD_{bft}) \times RL_{bft}$		-4.5***
		(1.4)
$RL_{bft} \times \text{Spe}_{bs(f)t}$	49.1**	55.4***
	(19.2)	(20.2)
$\ln(PD_{bft}) \times RL_{bft} \times \text{Spe}_{bs(f)t}$		22.8*
		(11.9)
Relationship controls	Yes	Yes
Firm controls	Yes	Yes
NACE-2D-Time FEs	Yes	Yes
Province-Time FEs	Yes	Yes
Bank-Time FEs	Yes	Yes
Observations	738,126	738,126
Adjusted R^2	0.15	0.15

Notes: Table reports estimated coefficients of interest from specifications based on:

$$\begin{aligned}\widetilde{R}_{ft} = \alpha &+ \beta_0 \cdot \ln(PD_{bft}) + \beta_1 \cdot RL_{bft} + \beta_2 \cdot \text{Spe}_{bs(f)t} \\ &+ \beta_3 \cdot RL_{bft} \times \text{Spe}_{bs(f)t} + \beta_4 \cdot \ln(PD_{bft}) \times RL_{bft} + \beta_5 \cdot \ln(PD_{bft}) \times \text{Spe}_{bs(f)t} \\ &+ \beta_6 \cdot \ln(PD_{bft}) \times RL_{bft} \times \text{Spe}_{bs(f)t} + \beta_7 \cdot \mathbf{X}_{bft} + \beta_8 \cdot \mathbf{X}_{ft-1} + \eta_{bt} + \eta_{s(f)t} + \eta_{p(f)t} + \varepsilon_{bft},\end{aligned}$$

where $\widetilde{R}_{ft}$ is the ratio of firm f's interest expense to financial debts and serves as a proxy for firm f's average interest rate, using single creditor firms only. RL_{bft} is the relationship length between firm f and bank b, PD_{bft} is firm f's default probability assessed by bank b, and $Spe_{bs(f)t}$ is a measure of excess bank specialization in sector s defined in Section 2.3 Firm-level controls ($\mathbf{X}_{ft-1}$) are total number of lenders, log-assets, cash/assets, intangibles/assets, net working capital/assets, equity/liabilities, retained earnings/assets, EBIT/assets, sales/assets, all lagged one year, and firm age deciles. Relationship controls ($\mathbf{X}_{bft}$) are log-outstanding credit, and log-collateral. Specifications include bank-by-time, firm NACE-2D industry-by-time, and firm province-by-time fixed effects. Estimation sample is an annual panel of bank-firm relationships from the Belgian Corporate Credit Register (CCR) over the period 2012-2021 using term loans and credit lines (cf. Appendix A.2). Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table C.6: Risky Firms Are Subject to Stronger Invest-Harvest:
Robustness to Predicted Measures of Firm Riskiness

Outcome	R_{bfct}			
x_{bft}	Predicted PD	$\mathbb{P}$(past due)	$\mathbb{P}$(expected def.)	$\mathbb{P}$(forbear.)
	(1)	(2)	(3)	(4)
x_{bft}	16.1***	3.1***	5.0***	3.8***
	(0.73)	(0.20)	(0.23)	(0.30)
RL_{bft}	8.0***	5.0***	4.1***	4.8***
	(0.44)	(0.51)	(0.39)	(0.40)
$\text{Spe}_{bs(f)t}$	-18.2***	-23.3***	-21.7***	-24.8***
	(1.9)	(2.7)	(2.4)	(3.8)
$x_{bft} \times RL_{bft}$	1.4***	-0.37**	-1.2***	-1.6***
	(0.44)	(0.15)	(0.17)	(0.17)
$RL_{bft} \times \text{Spe}_{bs(f)t}$	4.5**	9.3***	6.3***	6.9***
	(2.2)	(2.7)	(2.1)	(2.5)
$x_{bft} \times \text{Spe}_{bs(f)t}$	-12.6***	-3.5***	-4.5***	-4.0**
	(2.7)	(0.79)	(0.91)	(1.7)
$x_{bft} \times RL_{bft} \times \text{Spe}_{bs(f)t}$	7.1***	2.9***	3.4***	2.2*
	(2.7)	(0.86)	(0.97)	(1.2)
Contract controls	Yes	Yes	Yes	Yes
Relationship controls	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Bank-Time FEs	Yes	Yes	Yes	Yes
Observations	533,834	426,960	474,763	411,970
Adjusted R^2	0.61	0.59	0.61	0.58

Notes: Table reports estimated coefficients of interest from specification (2), where x_{bft} are predicted default probabilities (PDs) using observed PDs in a linear model in column (1) or realized past due payments, expected firm default, and forbearance status in a logistic model in columns (2), (3), and (4) respectively (cf. Section 3.3). R_{bfct} is the interest rate in basis points charged by bank b to firm f for credit contract c at time t, RL_{bft} is the relationship length between firm f and bank b, and $Spe_{bs(f)t}$ is a measure of excess bank specialization in sector s defined in Section 2.3. Specialization is centered and scaled by the average top sector specialization across banks and RL_{bft} is scaled by its standard deviation. Contract controls ($\mathbf{X}_{bfct}$) are log-authorized credit and contract maturity. Relationship controls ($\mathbf{X}_{bft}$) are default probability deciles, log-outstanding credit, and the number of outstanding contracts. Firm-level controls ($\mathbf{X}_{ft-4}$) are total number of lenders, log-assets, cash/assets, intangibles/assets, net working capital/assets, equity/liabilities, retained earnings/assets, EBIT/assets, sales/assets, all lagged one year, and firm age deciles. Specifications include bank-by-time, firm NACE-2D industry-by-time, and firm province-by-time fixed effects. Bank-contract-level fixed effects (η_{bc}) are interest rate type, instrument purpose, instrument repayment rights, origination vs. renegotiation indicator, and a collateralized indicator, all interacted with bank fixed effects (cf. Appendix A.1). Quarterly contract-level estimation sample uses credit lines and term loans at origination and renegotiation from IRB banks between 2018 Q4 and 2023 Q4. Sourced from BECRIS, Belgium's AnaCredit (cf. Appendix A.2). Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table C.7: Risky Firms Are Subject to Stronger Invest-Harvest:
Robustness to Firm Characteristics

Outcome	R_{bfct}				
	(1)	(2)	(3)	(4)	(5)
x_{ft}	EBIT/A	Sales/A	NWC/A	Cash/A	Z-score
x_{ft}	-0.13***	0.03***	0.02	-0.38***	-1.1***
	(0.02)	(0.01)	(0.01)	(0.02)	(0.30)
RL_{bft}	6.2***	8.2***	5.3***	4.6***	4.4***
	(0.35)	(0.43)	(0.35)	(0.38)	(0.44)
$\text{Spe}_{bs(f)t}$	-29.9***	-36.8***	-25.5***	-28.2***	-34.2***
	(3.0)	(4.0)	(2.9)	(3.2)	(3.8)
$x_{ft} \times RL_{bft}$	0.02	-0.05***	0.06***	0.15***	1.6***
	(0.02)	(0.008)	(0.009)	(0.02)	(0.27)
$x_{ft} \times \text{Spe}_{bs(f)t}$	0.84***	0.38***	0.16**	0.41***	9.1***
	(0.15)	(0.07)	(0.08)	(0.11)	(1.9)
$RL_{bft} \times \text{Spe}_{bs(f)t}$	8.6***	17.1***	9.2***	7.7***	14.8***
	(2.2)	(2.9)	(2.2)	(2.4)	(2.9)
$x_{ft} \times RL_{bft} \times \text{Spe}_{bs(f)t}$	-0.49***	-0.33***	-0.25***	-0.24**	-8.0***
	(0.15)	(0.05)	(0.06)	(0.11)	(1.8)
Contract controls	Yes	Yes	Yes	Yes	Yes
Relationship controls	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes
Bank-Time FEs	Yes	Yes	Yes	Yes	Yes
Observations	502,298	502,298	502,298	502,298	515,416
Adjusted R^2	0.61	0.61	0.61	0.61	0.61

Notes: Table reports estimated coefficients of interest from specification (2), where x_{ft} is either return on assets (column 1), sales/assets (column 2), net working capital/assets (column 3), cash/assets (column 4), or the firm's Altman Z-score (column 5). R_{bfct} is the interest rate in basis points charged by bank b to firm f for credit contract c at time t, RL_{bft} is the relationship length between firm f and bank b, and $Spe_{bs(f)t}$ is a measure of excess bank specialization in sector s defined in Section 2.3. Specialization is centered and scaled by the average top sector specialization across banks and RL_{bft} is scaled by its standard deviation. Contract controls ($\mathbf{X}_{bfct}$) are log-authorized credit and contract maturity. Relationship controls ($\mathbf{X}_{bft}$) are default probability deciles, log-outstanding credit, and the number of outstanding contracts. Firm-level controls ($\mathbf{X}_{ft-4}$) are total number of lenders, log-assets, cash/assets, intangibles/assets, net working capital/assets, equity/liabilities, retained earnings/assets, EBIT/assets, sales/assets, all lagged one year, and firm age deciles. Specifications include bank-by-time, firm NACE-2D industry-by-time, and firm province-by-time fixed effects. Bank-contract-level fixed effects (η_{bc}) are interest rate type, instrument purpose, instrument repayment rights, origination vs. renegotiation indicator, and a collateralized indicator, all interacted with bank fixed effects (cf. Appendix A.1). Quarterly contract-level estimation sample uses credit lines and term loans at origination and renegotiation from IRB banks between 2018 Q4 and 2023 Q4. Sourced from BE-CRIS, Belgium's AnaCredit (cf. Appendix A.2). Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table C.8: Firms Benefit from Relationships with Specialized Lenders: Relationship Fixed Effects

Outcome	Earn/A (1)	Retained/A (2)	Cash/A (3)	Equity/A (4)	NWC/A (5)	Trade cre/A (6)
RL_{bft}	-0.80***	-0.08	-1.2***	-0.79	-2.9***	-0.45
	(0.29)	(0.13)	(0.40)	(0.87)	(1.0)	(0.45)
$\text{Spe}_{bs(f)t}$	-0.36*	0.05	-0.41*	-0.75	-1.1*	0.26
	(0.19)	(0.07)	(0.22)	(0.57)	(0.60)	(0.26)
$RL_{bft} \times \text{Spe}_{bs(f)t}$	0.20*	-0.01	0.25**	0.94***	1.2***	-0.01
	(0.10)	(0.03)	(0.13)	(0.34)	(0.35)	(0.14)
NACE-2D-Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Province-Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Relationship FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,409,155	3,400,946	3,470,747	3,442,162	3,442,193	3,439,029
Adjusted R^2	0.27	0.30	0.62	0.66	0.65	0.59

Notes: Table reports estimated coefficients of interest from:

$$y_{ft} = \alpha + \beta_0 \cdot RL_{bft} + \beta_1 \cdot \text{Spe}_{bs(f)t} + \beta_2 \cdot RL_{bft} \times \text{Spe}_{bs(f)t} + \eta_{bt} + \eta_{s(f)t} + \eta_{p(f)t} + \eta_{bf} + \varepsilon_{bft},$$

where y_{ft} is a measure of firm outcome, i.e., earnings/assets (column 1), retained earnings/assets (column 2), cash/assets (column 3), equity/assets (column 4), net working capital/assets (column 5), net trade credit/assets (column 6). RL_{bft} is the relationship length between firm f and bank b, PD_{bft} is firm f's default probability assessed by bank b, and $Spe_{bs(f)t}$ is a measure of excess bank specialization in sector s defined in Section 2.3. Specialization is centered and scaled by the average top sector specialization across banks and RL_{bft} is scaled by its standard deviation. Specifications include bank-by-time, firm NACE-2D, firm province-by-time, and relationship fixed effects. Estimation sample is an annual panel of bank-firm relationships from the Belgian Corporate Credit Register (CCR) over the period 2012-2021 using term loans and credit lines (cf. Appendix A.2). Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table C.9: Specialized-Financed Firms Are More Productive: Relationship Fixed Effects

Outcome	EBIT/A (1)	Sales/A (2)	CapEx/A (3)	Inputs/A (4)	Materials/A (5)	ln(Payroll) (6)
RL_{bft}	-0.87**	-1.5*	-0.58***	-0.43	0.10	0.07**
	(0.37)	(0.87)	(0.17)	(0.74)	(0.61)	(0.04)
$\text{Spe}_{bs(f)t}$	-0.32	-1.0**	-0.32***	-0.82**	-0.50*	0.02
	(0.21)	(0.45)	(0.12)	(0.35)	(0.29)	(0.02)
$RL_{bft} \times \text{Spe}_{bs(f)t}$	0.22**	0.79***	0.24***	0.53**	0.37**	-0.006
	(0.11)	(0.27)	(0.06)	(0.21)	(0.17)	(0.01)
NACE-2D-Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Province-Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Relationship FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,408,151	3,180,451	1,531,189	3,189,078	3,189,224	2,144,089
Adjusted R^2	0.31	0.71	0.17	0.73	0.76	0.85

Notes: Table reports estimated coefficients of interest from:

$$y_{ft} = \alpha + \beta_0 \cdot RL_{bft} + \beta_1 \cdot \text{Spe}_{bs(f)t} + \beta_2 \cdot RL_{bft} \times \text{Spe}_{bs(f)t} + \eta_{bt} + \eta_{s(f)t} + \eta_{p(f)t} + \eta_{bf} + \varepsilon_{bft},$$

where y_{ft} is a measure of firm outcome, i.e., change in EBIT/assets (column 1), sales/assets (column 2), CapEx/assets (column 3), inputs/assets (column 4), materials/assets (column 5), payroll/assets (column 6). RL_{bft} is the relationship length between firm f and bank b, PD_{bft} is firm f's default probability assessed by bank b, and $Spe_{bs(f)t}$ is a measure of excess bank specialization in sector s defined in Section 2.3. Specialization is centered and scaled by the average top sector specialization across banks and RL_{bft} is scaled by its standard deviation. Specifications include bank-by-time, firm NACE-2D, firm province-by-time, and relationship fixed effects. Estimation sample is an annual panel of bank-firm relationships from the Belgian Corporate Credit Register (CCR) over the period 2012-2021 using term loans and credit lines (cf. Appendix A.2). Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.