Bank Specialization and Credit Relationships in Small-Business Lending*

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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

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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 where lenders learn about their borrowers through repeated interactions (Petersen and Rajan, 1994; Berger and Udell, 1995). Relationship lenders still face ex-ante information asymmetries which they can further mitigate by relying on knowledge gained from lending to similar borrowers in their area of specialization (Boot and Thakor, 2000; Berger, Minnis and Sutherland, 2017).

Lenders specialized in financing specific segments of the credit market offer more favorable loan terms to their borrowers (Blickle, Parlatore and Saunders, 2024). They 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 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. First, using micro-level data on the universe of corporate credit in Belgium, 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 and the US, small businesses are defined as enterprises employing up to 49 persons and 500 employees respectively.

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. While data on small-business lending is notoriously scarce, credit institutions in Belgium are not subject to any minimum reporting thresholds, allowing us to capture the entire distribution which—as in every country—is heavily skewed toward smaller firms. Additionally, we address the inherent riskiness of lending to opaque small businesses by leveraging firm-level default probabilities internally assessed by lenders under the Basel II Internal Ratings-Based (IRB) approach. On the credit supply side, Belgian banks hold specialized lending portfolios (De Jonghe et al., 2020; De Jonghe, Mulier and Samarin, 2024). Industry specialization is prevalent even among the four largest four banks which capture over 90% of total lending.[2] Therefore, the Belgian banking landscape provides a unique setting to study the interplay between lender 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, Parlatore and Saunders (2024).[3] 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

[2] This evidence is consistent with patterns of lender specialization documented in the US by Blickle, Parlatore and Saunders (2024).

[3] 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, Güler and Pietrosanti (2024); Paravisini, Rappoport and Schnabl (2023); Blickle et al. (2024); Degryse et al. (2024).

their industries of specialization over the entire length of the relationship.

The main identification challenge is disentangling the pricing decisions of specialized banks over time from two types of selection. At the beginning of the relationship, the lower rates charged by banks in their industries of specialization could be the 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.[4]

The trajectory of interest rates suggests that specialized lenders develop market power over the course of their relationship with their borrowers. 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 benefit from specialized relationships through industry-tailored products and lender expertise (Paravisini, Rappoport and Schnabl, 2023). This local monopoly power derived from differentiated credit 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

[4] 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.

relationships. We reconcile this result with theories of rent extraction à la Petersen and Rajan (1995) by deducing that lenders have more industry knowledge in their preferred sectors (Berger, Minnis and Sutherland, 2017; Blickle, Parlatore and Saunders, 2024; Bonfim et al., 2024). Better information-acquisition technologies translate into lower screening and monitoring costs for specialized lenders, keeping interest rates low despite the underlying rent extraction.

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 more generally for relationship-dependent borrowers, such as firms with fewer lenders and more contracts 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 5, 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.[5] 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).[6] 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).[7] The literature on bank specialization establishes that lenders develop market-specific knowledge by specializing in certain segments of the credit market and points out the benefits of bank specialization.[8,9] 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 loan terms early on.

Second, our work advances the literature on the long-term effects of information and

[5] 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).

[6] 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).

[7] 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.

[8] 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).

[9] Specialized lenders give larger amounts, lower rates and less restrictive financial covenants (Berger, Minnis and Sutherland, 2017; Blickle, Parlatore and Saunders, 2024; Giometti, Güler and Pietrosanti, 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 et al., 2020; Jiang and Li, 2022).

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, 1995; Boot and Thakor, 2000).[10] Specialized banks also obtain informational advantages over their competitors by lending to specific segments of the credit market.[11] 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.[12]

Third, this paper adds to the literature on the benefits of bank specialization. While some theoretical work argues in favor of lender diversification to limit information asymmetries (Diamond, 1984; Boyd and Prescott, 1986), lenders generally benefit from specialization.[13] On the firm side, De Jonghe et al. (2020) document that following a funding shock, banks reallocate credit supply toward specialized sectors and Degryse et al. (2024) find that specialized lenders support corporate innovation that does not compete with their existing loan portfolio. We contribute by showing that small businesses that 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.[14] 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 formulates 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 lays out our main re-

[10] 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.

[11] 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).

[12] 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.

[13] 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).

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

sults on the dynamic behavior of specialized banks throughout their relationships. Section 4 shows that specialized banks build and retains relationships with riskier borrowers. Section 5 studies the effect of specialization on firms' real outcomes. Section 6 concludes.

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.[15]

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 bor-

[15] 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.

rowers. They internalize the intertemporal value of relationships and attract borrowers by initially offering lower rates.[16] Lenders understand that the short term revenue loss from offering teaser rates early on is offset by the higher expected future revenues from 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 The invest-harvest behavior of specialized banks is reflected in firms decisions to terminate their relationships.

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.

[16] 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.

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.

2 Bank Specialization and Credit Relationships in Belgium

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

2.1 Data

We use regulatory data on the universe of corporate credit in Belgium from the *Belgian Extended Credit Risk Information System* (BECRIS) maintained by the National Bank of Belgium (NBB) between 2018 Q3 to 2023 Q4. This credit registry is the Belgian implementation of the *Analytical Credit Datasets* (AnaCredit) initiated by the European Central Bank (ECB), providing harmonized credit data collection guidelines across the Eurozone. Credit institutions report extensive information at the credit instrument level about attributes, protections provided, securitization status, performance, as well as all the counterparties involved (e.g., debtor, creditor, originator, servicer).[17,18]

Besides its granularity, BECRIS offers a wide scope. Every credit institution operating in Belgium reports its entire credit stock, regardless of the type of contract or debtor.[19] 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 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

[17] BECRIS and Anacredit distinguish between credit instruments and credit contracts since one contract can include several instruments. While our analysis is at the instrument level, we use both terms interchangeably.

[18] Loan applications, fees, and covenants are not reported.

[19] These credit institutions include Belgian branches of foreign institutions and subsidiaries of foreign banks incorporated in Belgium.

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), BECRIS' predecessor, which runs from 2012 Q2 to 2021 Q4.[20] While interest payments are not recorded, the CCR contains total outstanding credit amounts at the bank-firm relationship level. We can thus extend our series of bank specialization over a longer horizon when studying relationship formations, separations, and firm outcomes.

Finally, we collect balance sheet and income statement data on every limited liability firm in Belgium from the *annual accounts* (AA) reported annually to the NBB. We supplement these data with confidential VAT and Social Security declarations to obtain more accurate measures of firm sales, investment, input costs, and employment. While commonly available for large public firms, data on small business finances are rarely accessible. We leverage these firm characteristics to control for observable differences across borrowers and study the real effects of bank specialization. Appendix A reports additional details about the data cleaning procedures, sample selection, and variable definitions for each dataset.

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.[21] 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.

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. Appendix B provides further institutional background on the implementation of the IRB framework in Europe and evidence about the performance of these default probabilities. Overall, one-year ahead default probabilities estimated by IRB credit institutions ideally proxies for firms default risk.

[20] 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.

[21] 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.

2.2 Credit Relationships in the Corporate Credit Market

The Belgian corporate credit market is asymmetrical. First, the supply of credit is concentrated. Out of 25 lenders in BECRIS, the largest four banks account for about 90% of total outstanding credit. While 13 banks report default probabilities as part of the IRB approach, they account for 96% of total credit. Table 1 provides additional summary statistics on lenders outstanding credit stock (panel A) and credit flows (panel B). On average, banks have 12,700 borrowers, 13% of which are new relationships. Out of 88 NACE-2D divisions, banks operate in 54 on average and thus strike a balance between diversification and specialization. While their lending portfolios are not fully diversified, they also do not focus on a few industries.

Second, the demand for corporate credit mostly emanates from small businesses. Table 2 presents firm-level summary statistics. Out of over 350,000 firms in the sample, small and micro enterprises with less than 49 persons represent 99% of firms and capture 80% of total credit. 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 nor capital expenditures. Thus, this median firm is best described as a local small business, operating as a one-person shop. On the financing side, the median firm has 1.5 outstanding debt contracts on average across all its lenders, totaling about €150,000, and takes out a new contract every 10 months.

Small businesses develop strong credit relationships with their lenders. 85% of firms borrow from a single lender, 40% have a single contract, and the median relationship length is five years.[22] These credit relationship are provided not only by smaller banks. Figure 1 plots the distribution of relationship lengths split between the Big Four banks and the other banks. Both groups of lenders have similar relationship lengths with their respective borrowers.

Small businesses rely on bank credit as a primary source of external financing due to the lack of access to public financing markets. In Belgium, 108 issue public equity and 71 firms issue bonds. Besides, while non-bank financial intermediaries (NBFIs) have been providing increasingly more financing to non-financial corporations (NFCs) since the global financial crisis in the euro area, they mostly focus on public debt securities for large enterprises (Cappiello et al., 2021). In comparison, debt securities account for about 1% of small and medium-sized enterprises' liabilities while bank loans account for over 20%. Given the absence of alternative funding opportunities, small businesses

[22] 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.

are more likely to be locked into a relationship with their banks. Lenders can use this local monopoly power to extract surplus from small businesses, in line with the holdup behavior empirically observed by Santos and Winton (2008).

While Belgium is an ideal setting to study credit relationships in small-business lending thanks to the granularity of its data, the patterns documented previously are valid in most developed economies. Both in the US and in the European Union, small businesses make up 99% of firms and rely on credit relationships to finance their activities (Jiménez et al., 2012; Popov and Udell, 2012; Cotugno, Monferrà and Sampagnaro, 2013; Deyoung et al., 2015; Duygan-Bump, Levkov and Montoriol-Garriga, 2015). While the Belgian credit market is dominated by four large banks, credit markets of comparable geographical areas can be concentrated.[23] The local nature of credit markets is relevant in this setting since small businesses are known to build credit relationships with geographically close lenders (Petersen and Rajan, 2002; Liberti and Mian, 2009; Agarwal and Hauswald, 2010).

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

[23] As a comparison, Belgium's GDP is similar to Massachusetts' and has a population equivalent to Ohio.

below).[24]

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,[25] 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 2 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 D.3 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

[24] 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 $w_b := \frac{L_b}{L}$.

[25] 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 movements in rates over a contract's life cycle—e.g., resulting from reference rate variations in the case of flexible rate contracts.[26] 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—charged by bank b to firm f on credit contract c, 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.[27]

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

[26] 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.

[27] 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.[28] 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 2. 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.[29] 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

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

[29] 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 C 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.

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 while they charge low interest rates. In the harvest period, lenders increase the relative maturity in their industries of specialization to benefit from the steeper rate increases for longer. Thus, banks dynamically adjust contract maturity in a way that is consistent with their invest-harvest behavior.

In Figure 3, 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.[30] 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-firm 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

[30] 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 give 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.[31] In column (5) we verify the stability of our results to bank-time and bank-firm fixed effects. In Appendix Table D.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) 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.[32]

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 supply. Eligible firms could apply for a six-month repayment deferral where only the loan

[31] 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)).

[32] In Appendix Table D.3, we verify the robustness of our results to alternative measures of specialization with contract maturity as outcome.

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 D.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 D.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 focusing on 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

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

where x_{bft} is a firm or relationship-level characteristic. We focus on three dimensions of borrower heterogeneity. First, in Figure 4 we decompose the invest-harvest behavior by loan size using quartiles of contracts' authorized amounts. Second, in Figure 5 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 6 we split borrowers into quartiles of default probability to understand the role of firm riskiness.[33]

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

[33] 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.

First, we use multiple predictive methods to estimate various alternative measures of firm riskiness independent of banks assessments.[34] In column (1) of Appendix Table D.6, we isolate the variation in default probabilities orthogonal to bank decisions by using the predicted values from an OLS regression on firm characteristics.[35] We also estimate default probabilities based on 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.

Second, in Appendix Table D.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-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

$$\begin{aligned} \mathbb{1}\{\text{rel. ends}_{bft}\} = \sum_q Q_q\{RL_{bft}\} \times \left(\alpha_q + \beta_{0q} \cdot \text{Spe}_{bs(f)t}\right) \\ + \beta_1 \cdot \mathbf{X}_{bft} + \beta_2 \cdot \mathbf{X}_{f0(b)} + \eta_{bt} + \varepsilon_{bft}, \end{aligned} \tag{3}$$

where $\mathbb{1}\{\text{rel. ends}_{bft}\}$ is an indicator variable equal to one when firm f ends its relationship with bank b, and $Q_q\{RL_{bft}\}$ is the fixed effect for the qth quintile of relationship length. Since our outcome of interest is at the bank-firm level, we draw our estimation

[34] 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.

[35] 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.

sample from the Corporate Credit Register (CCR) to benefit from the longer time period (2012 Q2-2021 Q4). We keep relationships with no signs of financial distress to avoid constrained separations and focus on cases where borrowers voluntarily choose to end their relationship.[36] The specification includes relationship, firm controls, and bank-time fixed effects to isolate separation decisions in response to lenders' invest-harvest behavior. Relationship controls ($\mathbf{X}_{bft}$) include fixed effects of default probability deciles, log-authorized credit, and log-collateral. 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.

The coefficients $\{\beta_{0q}\}_q$ measure differences in separation rates across lenders' industries of specialization for each bin of relationship length. The baseline specification estimates are plotted in red in Figure 7. Firms in banks' top industries are one percentage point less likely to end their relationship early on relative to firms in diversified sectors. This wedge eventually reverts; after five years of relationship, specialized-financed firms are one percentage point *more* likely to end their relationship than diversified-financed firms. Specialized-financed firms have consistently higher separation rates in the long run.

These separation patterns are consistent with the dynamics of interest rates that specialized lenders charge their borrowers. In the invest phase, specialized-financed firms are more likely to stay in their relationship to benefit from the low rates offered by specialized lenders. In the harvest phase, firms react to the rate increases of specialized lenders by increasingly terminating their relationships. Thus, the invest-harvest behavior of specialized banks is reflected in the firms' separation decisions.

We test the robustness of our results by adding firm-time fixed effects to compare the separation decisions of a given firm borrowing from multiple lenders with varying degrees of specialization. The estimates, plotted in blue in Figure 7, closely align with our previous results and confirm that these patterns are not due to firm-level factors unrelated to the credit relationship.

[36] We drop observations where the firm has a default probability above 95%, has past-due payments, or is flagged as unlikely to meet a repayment by its lender.

4 The Role of Bank Specialization In Risky Relationships

In this section, we show that lenders are more likely to develop credit relationships with risky firms in their areas of specialization. We argue that the ability of specialized lenders to build and retain risky relationships is consistent with the pattern of invest-harvest behavior established in Section 3.

4.1 Risky Firms Sort With Specialized Banks

In the invest phase, lenders offer increasingly large rate discounts to risky firms in their industries of specialization. We document the attractiveness of these specialized relationships for risky firms by analyzing the sorting patterns between lenders and borrowers. 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 that industry over a given quarter.[37] We estimate

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

where $\mathbb{1}\{\text{Rel. start}_{bft}\}$ is an indicator variable of a match between firm f and bank b, and x_{ft-4} is some firm characteristic affecting the likelihood of a match. We use the 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 lenders' baseline match probabilities, and sector-time ($\eta_{s(f)t}$) and province-time ($\eta_{p(f)t}$) fixed effects control for firms' abilities to form new relationships in specific industries or locations.[38] The coefficient β_1 is the baseline effect of an increase in lender specialization on the match probability, and the coefficient of interest β_2 measures the effect of firm characteristic x_{ft-4} on the match probability with a specialized bank.

Table 7 presents the estimation results for each standardized firm characteristic. In column (1), we find that firms with an average Z-score are 1.2 percentage points more likely to start a relationship when they belong to their lender's top industry compared

[37] We do not observe loan applications, therefore our data does not capture firms looking for credit that did not find a match. We do not define an outside option to avoid making arbitrary choices about which firm is looking for a new relationship. Thus, every firm ends up finding a match in our data.

[38] Since every firm finds a match in our data, controlling for firm characteristics or adding firm fixed effects does not bear any meaningful interpretation.

to its diversified industries. A one-standard deviation increase in the firm's Z-score is associated with a 0.08 percentage point reduction in the match probability with a specialized bank. While specialized lenders 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, as well as higher intangible assets are more likely to match with specialized lenders. Therefore, riskier firms are more likely to start a specialized relationship.

The sorting of risky firms with specialized lenders may seem at odds with Section 3.3 where we show that lenders assign similar default probabilities regardless of their specialization level. In the former case, we analyze the matching patterns of *disctinct* firms based on their characteristics. In the latter case, we use firm-time fixed effects in our specification so this result is conditional on multiple lenders matching with the *same* borrower.

The observed matching patterns could be driven by banks or firms. Risky firms might be unaware of the presence of less specialized lenders in their industry and could bias their credit demand toward specialized lenders. Non-specialized lenders might also lack the knowledge to effectively screen risky borrowers, resulting in more specialized relationships ex-post. However, we argue that the sorting between risky firms and specialized lenders is not driven by demand factors for two reasons. First, the Big Four banks capture 90% of total corporate credit in Belgium, so it is unlikely that risky firms are unaware of lender alternatives. Second, search frictions and adverse selection would reduce lender competition and give specialized lenders greater market power in the pre-match phase, allowing them to raise markups. On the contrary, we find that risky firms benefit from larger rate discounts in their lenders' areas of specialization. We instead attribute these matching patterns to specialized banks successfully attracting more vulnerable borrowers with lower rates, in line with the information-based channel of specialization formulated by Blickle et al. (2024).

Finally, the sorting patterns documented in this section confirm the concern evoked in Section 3.1 that certain borrowers select into relationships with specialized lenders. This evidence highlights the importance of accounting for selection, which we address by leveraging the richness of our data. While some selection on unobservables might persist after controlling for these characteristics, it does not bias our results given their robustness to relationship fixed effects and firm-time fixed effects.

4.2 Risky Firms Have Longer Relationships With Specialized Lenders

In the harvest phase, banks raise rates faster in their industries of specialization, and even faster still for riskier firms. Despite these hikes, we document that specialized banks maintain relationships with risky borrowers longer. We explore voluntary relationship endings by building a sample of relationships with observed end dates and where borrowers shows no signs of financial distress.[39] We estimate

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

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 in quarter T when the relationship ended. 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. Bank-time fixed effects (η_{bt}) absorb banks propensities to end relationships.

Baseline estimation results are reported in column (1) of Table 8. Borrowers with a one percent default probability separate on average 7.5 months later if they belong to their lender's top industry of specialization compared to a diversified industry.[40] A one-percent increase in default probability is associated with a 2.4-month later separation for firms belonging to the bank's top industry. In column (2), we augment our specification with sector-time and province-time fixed effects to control for industry and location-specific separations trends while, in column (3), firm-time fixed effects control for any firm-level factors affecting relationship endings. Our results are unchanged, meaning that a firm borrowing from multiple lenders stays longer with its more specialized lenders.

The ability of specialized banks to retain riskier firms despite their stronger harvest behavior could be due to the fact that specialized-financed firms obtain lower rates than firms borrowing from non-specialized lenders. We decompose the separation patterns of riskier firms throughout the length of their relationship by augmenting specification (3)

[39] A relationship is considered over when no interaction is reported for the next five years. We drop endings where the firm has a default probability above 95%, has past-due payments, or is flagged as unlikely to meet a repayment by its lender.

[40] The average overall relationship length is 4.1 years in this sample.

and estimating

$$\mathbb{1}\{\text{rel. ends}_{bft}\} = \sum_q Q_q\{RL_{bft}\} \times \Big(\alpha_q + \beta_{0q} \cdot \ln(PD_{bft}) + \beta_{1q} \cdot \text{Spe}_{bs(f)t} + \beta_{2q} \cdot \ln(PD_{bft}) \times \text{Spe}_{bs(f)t}\Big) + \beta_3 \cdot \mathbf{X}_{bft} + \beta_4 \cdot \mathbf{X}_{f0(b)} + \eta_{bt} + \varepsilon_{bft}. \tag{6}$$

Figure 8 plots the estimates for $\{\beta_{1q}\}_q$ and $\{\beta_{2q}\}_q$. Similar to Figure 7, panel (a) shows that the separation patterns of safe firms mirror the invest-harvest behavior of specialized lenders. Compared to diversified relationships, safe firms in specialized relationships are less likely to separate early on, and more likely after four years. In panel (b), we find that riskier firms are always less likely to end their relationship with specialized lenders, especially early on when specialized lenders invest in these risky relationships. Moreover, despite specialized lenders exerting stronger harvest later on, the separation rates of riskier firms are increasingly smaller. Therefore, the propensity of risky firms to stay longer in specialized relationships is not solely due to specialized lenders offering more competitive rates.

The fact that risky firms stay longer in specialized relationships despite the stronger harvest behavior of specialized banks could be due to two other forces. First, risky borrowers might face higher costs of terminating specialized relationships. The informational gap of starting a new relationship with a less informed non-specialized lender exacerbates the holdup problem faced by riskier firms, as documented by Santos and Winton (2008). This adverse selection problem pushes risky firms to stay in their current relationship.

Second, small businesses derive non-price benefits from their specialized relationships (Paravisini, Rappoport and Schnabl, 2023), especially risky firms being less financially sophisticated.[41] Specialized lenders provide insights about regulation and supply-chain management specific to the firms industry. They also use custom underwriting to tailor credit contracts to the needs of their borrowers and better match the reality of their business. This bundling of industry-specific expertise and funding means that credit is non-fungible between lenders. Risky firms that value this differentiated credit from specialized lenders are therefore willing to pay a markup to stay in a specialized relationship.

Finally, the separation patterns documented in this section confirm the concern raised in Section 3.1 that selected attrition confounds banks pricing decisions. The observed

[41] The median firm in our sample does not have any employees, thus the owner is responsible for managing its finances on top of her primary activity much like a household.

dynamics of interest rates charged by specialized lenders could be the result of riskier borrowers selecting into long, specialized relationships, and specialized lenders charging higher risk premia to these borrowers. Thus, firm-level default probabilities are an important tool to isolate the pricing decisions of specialized lenders independent of risk-based considerations.

5 The Real Effects of Bank Specialization

The literature has established that lenders benefit from holding a specialized portfolio instead of a diversified one (Acharya, Hasan and Saunders, 2006; Jahn, Memmel and Pfingsten, 2016; Gelman, Goldstein and MacKinlay, 2023). While borrowers are known to obtain better financing conditions and expertise from specialized lenders (De Jonghe, Dewachter and Ongena, 2020; Duquerroy et al., 2022; Paravisini, Rappoport and Schnabl, 2023; Blickle, Parlatore and Saunders, 2024; Bonfim et al., 2024), less is known about the real effects of specialization. Notable exceptions are De Jonghe, Mulier and Samarin (2024) and Degryse et al. (2024) in the context of zombie lending and corporate innovation. Do firms that stay in a relationship with a specialized lender experience better real outcomes? We estimate

$$\begin{aligned}\Delta y_{ft,0(b)} = \alpha + \beta_0 \cdot RL_{bft} + \beta_1 \cdot \text{Spe}_{bs(f)t} + \beta_2 \cdot RL_{bft} \times \text{Spe}_{bs(f)t} \\ + \beta_3 \cdot \mathbf{X}_{bft} + \beta_4 \cdot \mathbf{X}_{f0(b)} + \eta_{bt} + \eta_{s(f)t} + \eta_{p(f)t} + \varepsilon_{bft},\end{aligned} \quad (7)$$

where $\Delta y_{ft,0(b)}$ measures the growth in firm f's outcome over the course of its relationship with bank b. We use growth rates to remove concerns about specialized banks sorting with certain types of borrowers as documented in Section 4.1. Relationship controls ($\mathbf{X}_{bft}$) are default probability deciles fixed effects, log-outstanding credit, and log-collateral. Firm controls ($\mathbf{X}_{f(0)b}$) are identical to specification (1) and measured at the start of the relationship.

Table 9 reports the estimation results using measures of firm profitability (change in earnings-over-assets in column 1), productivity (growth in sales-over-assets in column 2), investment (growth in capital expenditure in column 3), liquidity (growth in cash reserves, change in net working capital-over-assets in columns 4 and 6), and financial health (change in equity-over-assets in columns 5). The negative estimates for β_1 indicate that firms borrowing from specialized lenders have worse outcomes early in their relationships, in line with the propensity of specialized lenders to match with riskier firms documented in Section 4.1. Firms in specialized relationships subsequently have higher growth in profitability, productivity, investment, liquidity, and financial health. In particular, the earnings of specialized-financed firms growth faster despite their lenders exerting stronger harvest behavior.

The better real outcomes of specialized-financed firms could be due to firms with high growth-potential self-selecting into specialized relationships, or specialized lenders using their industry knowledge to pick these borrowers. To address these concerns, we augment specification (7) and replace industry-by-time and province-by-time fixed effects with relationship-level fixed effects. The effect of specialization is now identified within a given bank-firm relationship off variation in bank specialization over time. The estimation results are reported in Appendix Tables D.8.[42] Given these fixed effects, the better real outcomes of firms in specialized relationships suggest that these borrowers benefit from specialized lenders' monitoring abilities.

In the previous section, we discussed how the harvesting behavior of specialized banks could indicate that borrowers in specialized relationships face higher switching costs or value specialized products and expertise. If switching costs accounted for these lending patterns, specialization would be a zero-sum game. Lenders would take advantage of the information gap with outside lenders to extract surplus from relationships in their industries of specialization, while borrowers being held up would have worse real outcomes than firms borrowing from non-specialized banks.

Instead, better real outcomes suggest that small businesses derive benefits from their specialized relationships. Firms use the expertise and tailored products offered by specialized lenders to make better business decisions and operate more efficiently. Specialized lenders harvest some of this excess surplus in return by increasing their markups in the later stages of their relationships. Therefore, specialization is a positive-sum game between lenders and borrowers.

6 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

[42] We use firm outcomes in levels instead of growth rates since relationship fixed effects absorb the outcome's initial value.

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 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.

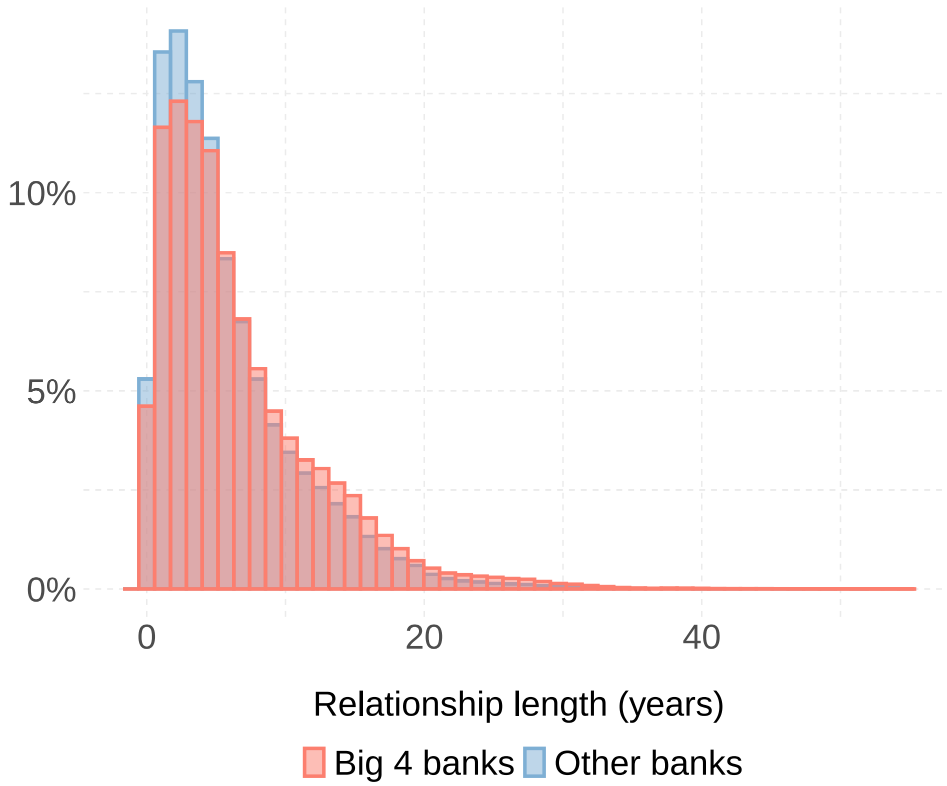


Figure 1

Notes: This figure plots histograms of relationships lengths between banks and their borrowers. 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).

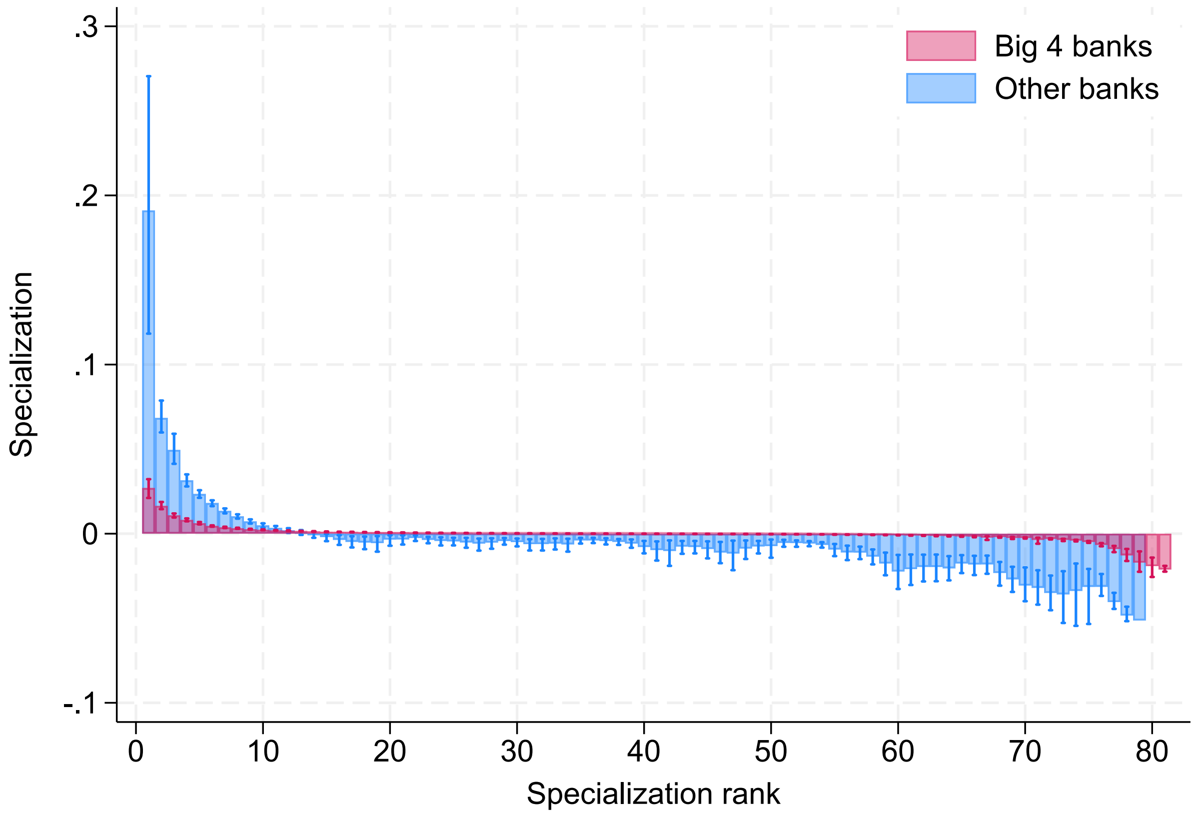
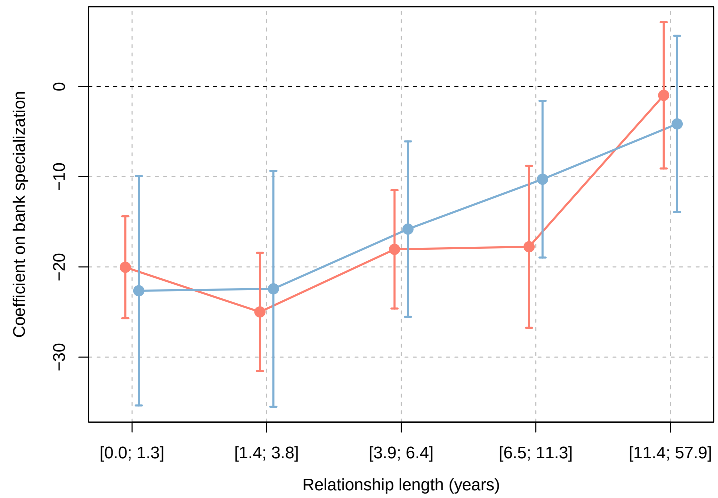
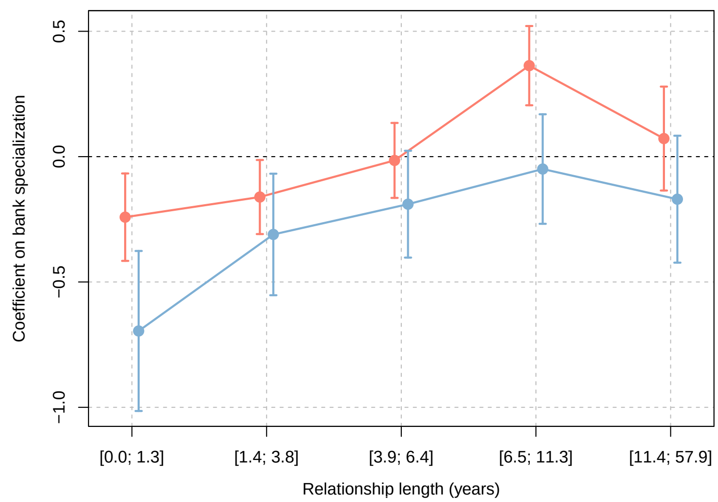


Figure 2: Average Specialization Split by Rank in Bank Portfolios

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).



(a) Interest Rates



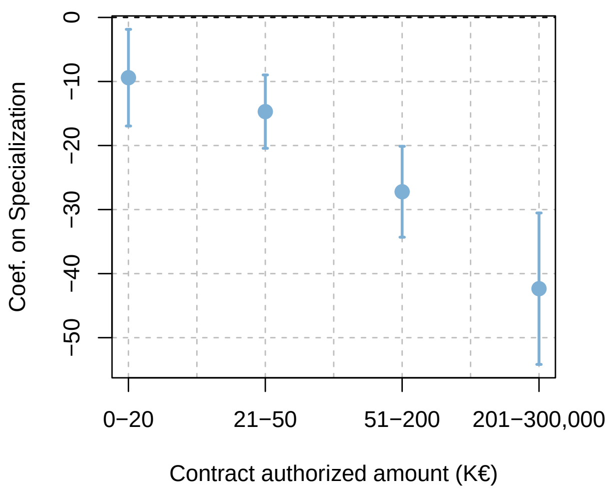
(b) Maturity

Figure 3: The Invest-Harvest Behavior of Specialized Banks

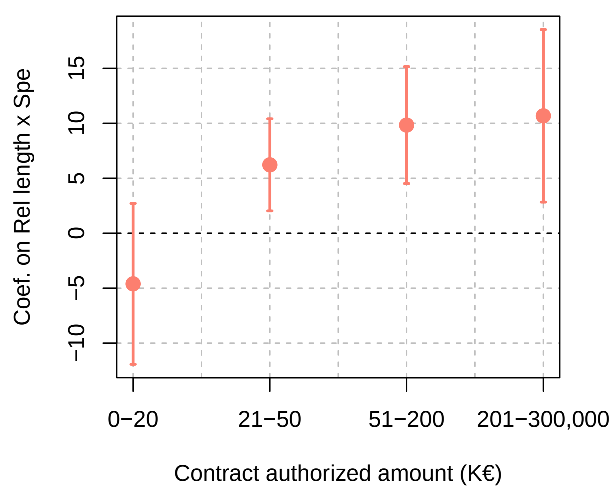
Notes: Figure plots estimated coefficients for $\{\beta_{1q}\}_{q=1}^{5}$ from:

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

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). 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



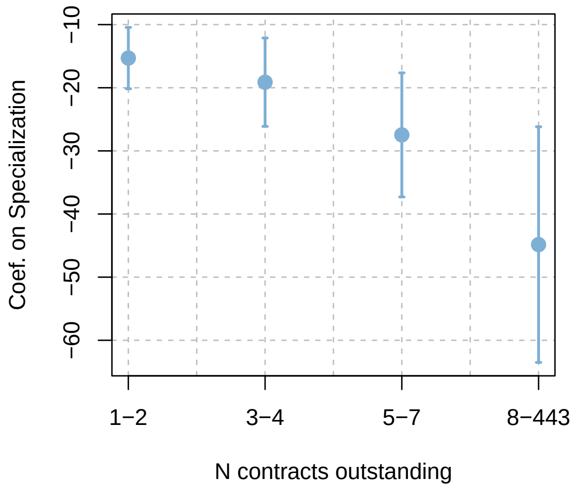
(b) Established Relationships

Figure 4: Large Contracts Are Subject to Stronger Invest-Harvest

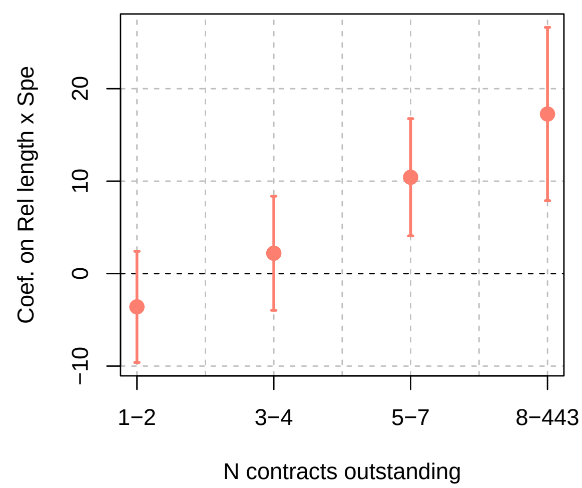
Notes: Figure plots estimated coefficients for $\{\beta_{1q}\}_{q=1}^{4}$ from:

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

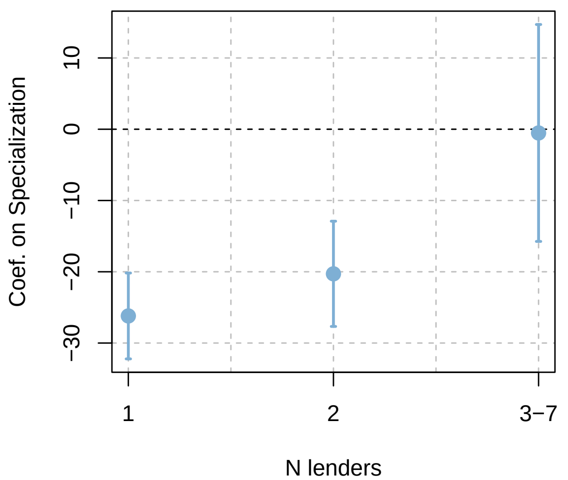
where $Q_q\{L_{bfct}\}$ is the fixed effect for the qth quartile of contract c's authorized amount. R_{bfct} is the interest rate in basis points charged by bank b to firm f for credit contract c at time t, RL_{bft} is the relationship length between firm f and bank b, $Spe_{bs(f)t}$ is a measure of 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. 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). Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.



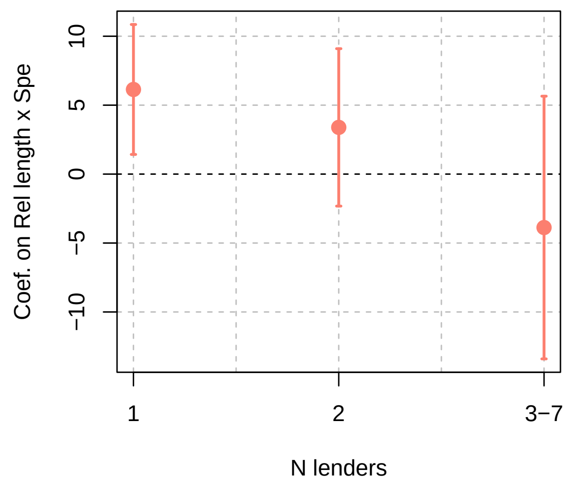
(a) New Relationships



(b) Established Relationships



(c) New Relationships



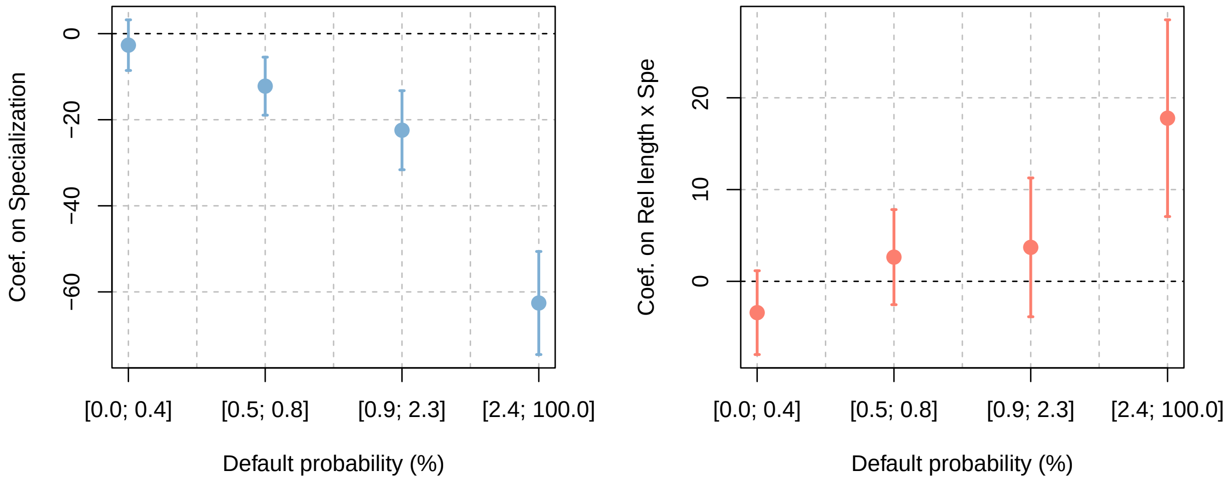
(d) Established Relationships

Figure 5: 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. Variable definitions and fixed effects are identical to Figure 4. 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). 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 6: 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. Variable definitions and fixed effects are identical to Figure 4. 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). Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

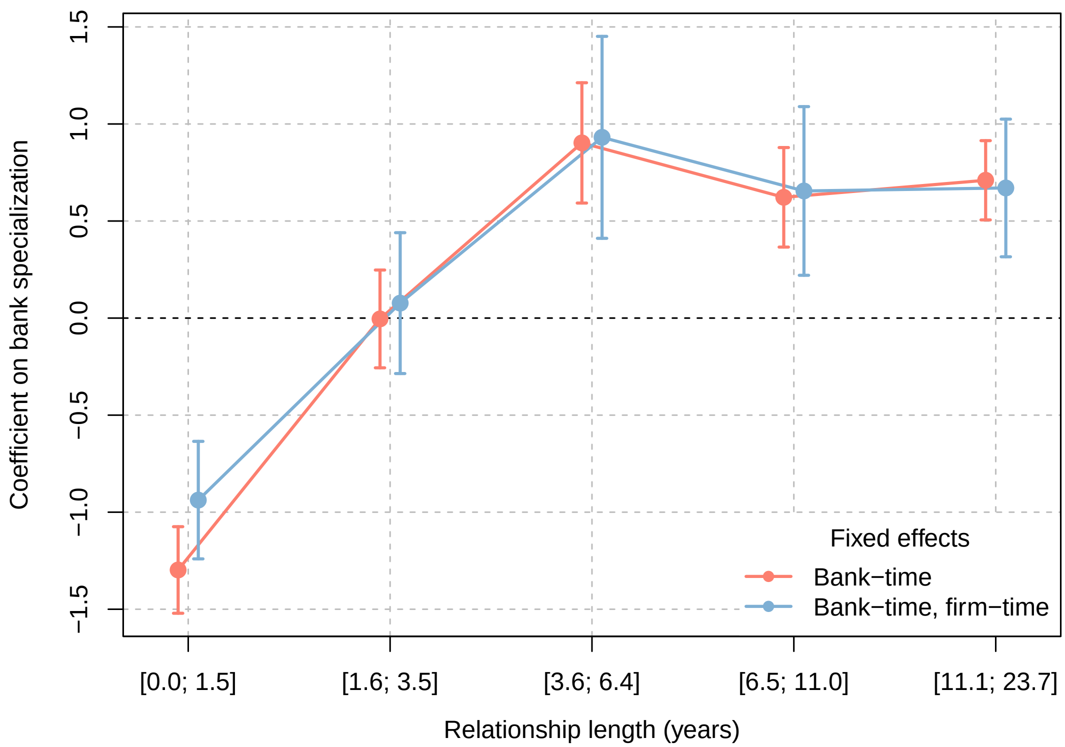
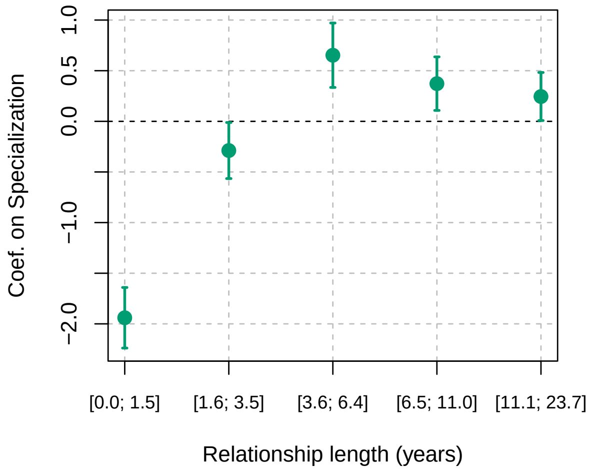


Figure 7: Effect of Invest-Harvest Behavior on Relationship Separations

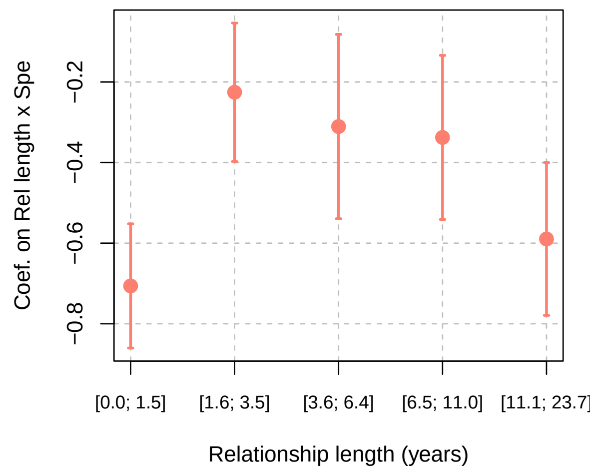
Notes: Figure plots estimated coefficients for $\{\beta_{0q}\}_q$ from:

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

where $\mathbb{1}\{\text{rel. ends}_{bft}\}$ is an indicator variable equal to one when firm f ends its relationship with bank b, and $Q_q\{RL_{bft}\}$ is the fixed effect for the qth quintile 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 default probability deciles fixed effects, 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. Red coefficient specifications use bank-time fixed effects, blue coefficient specifications include bank-time and firm-time 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). 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 8: Effect of Invest-Harvest Behavior on Relationship Separations

Notes: Figure plots estimated coefficients for $\{\beta_{1q}\}_q$, $\{\beta_{2q}\}_q$ from:

$$\mathbb{1}\{\text{rel. ends}_{bft}\} = \sum_q Q_q\{RL_{bft}\} \times \Big(\alpha_q + \beta_{0q} \cdot \ln(PD_{bft}) + \beta_{1q} \cdot \text{Spe}_{bs(f)t}$$
$$+\beta_{2q} \cdot \ln(PD_{bft}) \times \text{Spe}_{bs(f)t}\Big) + \beta_3 \cdot \mathbf{X}_{bft} + \beta_4 \cdot \mathbf{X}_{f0(b)} + \eta_{bt} + \varepsilon_{bft},$$

where $\mathbb{1}\{\text{rel. ends}_{bft}\}$ is an indicator variable equal to one when firm f ends its relationship with bank b, and $Q_q\{RL_{bft}\}$ is the fixed effect for the qth quintile of relationship length. Variable definitions are identical to Figure 7. Specification includes bank-by-time 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). 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.

Table 1: Banks Summary Statistics

	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. In panel A, *N borrowers* is the number of firms a lender has a credit relationship with, *N contracts* is the number of outstanding contracts on a lender's balance sheet in a given quarter, *NACE-2D industries* is the number of industries that a bank lends (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 B, *N borrowers* is the number of new borrowers in a given quarter and *N contracts* is the number of contracts originated. Quarterly sample sourced from BECRIS, Belgium's AnaCredit (cf. Appendix A).

Table 2: Firms Summary Statistics

	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: This table reports summary statistics between 2018 Q4 and 2023 Q4 for the sample of firms used in Section 3. See Appendix A for variables construction. Quarterly credit data sourced from BECRIS, Belgium's AnaCredit (cf. Appendix A); 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 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. 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). 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:

$$\begin{aligned}\text{Matur}_{bfct} &= \alpha + \beta_0 \cdot RL_{bft} + \beta_1 \cdot \text{Spe}_{bs(f)t} + \beta_2 \cdot RL_{bft} \times \text{Spe}_{bs(f)t} \\ &\quad + \beta_3 \cdot \mathbf{X}_{bfct} + \beta_4 \cdot \mathbf{X}_{bft} + \beta_5 \cdot \mathbf{X}_{ft-4} + \eta_{bc} + \eta_{bt} + \eta_{bf} + \varepsilon_{bfct},\end{aligned} \tag{8}$$

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 the interest rate. 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. 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). 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 variable definitions are identical to Table 3. 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). 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)
Geo $\text{spe}_{bp(f)t}$				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)
$RL_{bft} \times$ Geo $\text{spe}_{bp(f)t}$				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 $Spe_{bs(f)t}$ refers to various measures of bank industry specialization and other variable definitions are identical to Table 3. 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. 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). Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

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)
NACE-2D-Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank-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 specification (4), 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). 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 Lenders

Outcome	Overall RL_{bf}		
	(1)	(2)	(3)
$\ln(PD_{bft})$	-0.41***	-0.41***	-0.27***
	(0.009)	(0.009)	(0.03)
$\text{Spe}_{bs(f)t}$	0.63***	0.57***	0.45**
	(0.10)	(0.11)	(0.23)
$\ln(PD_{bft}) \times \text{Spe}_{bs(f)t}$	0.20***	0.30***	0.21*
	(0.04)	(0.04)	(0.12)
Relationship controls	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes
Bank-Time FEs	Yes	Yes	Yes
(NACE-2D & Province)-Time FEs		Yes	
Firm FEs			Yes
Observations	117,587	117,109	32,884
Adjusted R^2	0.40	0.41	0.46

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). 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(Earnings/A) (1)	$\Delta\log$(Sales/A) (2)	$\Delta\log$(CapEx) (3)	$\Delta\log$(Cash) (4)	Δ(Equity/A) (5)	Δ(NWC/A) (6)
RL_{bft}	0.11**	-4.8***	-18.5***	20.5***	23.0***	12.6***
	(0.05)	(0.19)	(1.2)	(0.48)	(0.29)	(0.22)
$\text{Spe}_{bs(f)t}$	-0.52	-3.4**	11.5	-9.2***	-1.9	-4.1***
	(0.34)	(1.4)	(9.8)	(3.2)	(1.7)	(1.4)
$RL_{bft} \times \text{Spe}_{bs(f)t}$	0.81***	1.7**	11.1**	6.5***	4.2***	5.0***
	(0.18)	(0.82)	(4.9)	(2.0)	(1.1)	(0.91)
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	1,352,283	599,158	1,369,159	1,367,389	1,364,907
Adjusted R^2	0.06	0.05	0.03	0.06	0.12	0.10

Notes: Table reports estimated coefficients of interest from specification (7), 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 default probability deciles fixed effects, 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. 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). Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

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Appendix

A Additional Data Description

This section outlines the data cleaning procedures, sample selection, and variable definitions for the datasets used throughout the paper.

A.1 Belgian Extended Credit Risk Information System (BECRIS)

Data cleaning. While each observation in BECRIS is at the bank-firm-contract-reporting month level, 6% of groups contain multiple observations. These duplicates are either identical or differ in their authorized amounts, with one of the observations having zero authorized amount. We thus keep observations with positive authorized amounts and drop other duplicate observations. Revolving credit such as credit lines or overdrafts have zero authorized amounts, so we use instead the largest used amount throughout the contract's lifetime whenever it does not go into forbearance. We also drop observations where authorized credit is likely miscoded by looking at firm debt in their balance sheet. These amounts are not directly comparable since firms file accounts annually and a borrower needs not to draw the entirety of the authorized amount. We thus adopt a conservative approach and drop borrowers with authorized amounts 10 times or used amounts 3 times larger than their total debt.

Sample selection. We keep unconsolidated banks with Belgian activity subject to regulatory filings at the NBB (Schema A) and our sample is restricted to quarters in which a bank has at least 100 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 standard credit institutions. Additionally, we drop borrowers that account for more than 5% of a bank's total lending. On the firm side, we include only Belgian non-financial firms—both limited and unlimited liability firms—excluding public sector entities, educational institutions, government bodies, and nonprofit organizations. Following the AnaCredit classification, we keep instruments of type "Revolving credit other than overdrafts and credit card debt", "Credit lines other than revolving credit", and "Other loans" (instrument codes 1001, 1002, and 1004) regardless of their characteristics (e.g., loan purpose, interest type, repayment rights) but restrict to contracts with positive interest rates and maturities. We drop default probabilities below 0.03% in line with AnaCredit guidelines. Finally, interest rate, contract maturity, and number of past interactions are trimmed at the 99% percentile.

Variable definitions. Credit institutions report inception dates for each of their contracts, which we use to construct our measure of relationship length. These dates allow us to observe relationships that began prior to the start of our sample period. We restrict inception dates to those after January 1st, 1955 and retain the most recent inception date when multiple dates are reported over a contract's lifetime. The start of a bank-borrower relationship is defined as the earliest inception date across all outstanding contracts between a bank and its borrower.

We use several categorical variables to account for differences in contract characteristics. *Interest rate type* can either be fixed, variable, mixed, or not applicable. *Instrument purpose* can be: margin lending, debt financing, imports, exports, construction investment, working capital facility, residential real estate purchase, commercial real estate purchase, or other. *Instrument repayment rights* can be on demand or short notice, other, or unknown.

A.2 Corporate Credit Register (CCR)

We replace authorized credit with used credit whenever authorized credit is either missing or smaller than used credit. As for BECRIS, we drop borrowers with authorized amounts 10 times or used amounts 3 times larger than their total debt reported in their Annual Account. We also apply the same sample selection criteria for banks, borrowers, and credit types.

Each observation in the CCR is recorded at the bank-firm-instrument type-maturity-month level which means that information on contract origination dates is not available. While our sample period begins in 2012—when lenders start reporting borrower-level default probabilities—the CCR dataset extends back to 1998. We construct relationship age by identifying the earliest month in which a bank reports lending to a given borrower. To avoid left-censoring, we exclude relationships that were already present in 1998. Firms may experience periods without outstanding credit from a given bank during the course of their relationship. We treat a relationship as terminated and a new one as initiated if the break in credit reporting exceeds five consecutive years. In Figure 7 we analyze relationship terminations by recording the last date a lender reports an outstanding credit amount for at least the next five consecutive years. We avoid right censoring by dropping ongoing relationships at the end of our sample period.

A.3 Annual Accounts (AA)

Only limited liability companies are required to file Annual Accounts, although unlimited liability firms may choose to do so voluntarily. We define firm debt as the sum between financial debts payable before and after one year. The Altman Z-score for private companies is constructed as $0.717 *$ net working capital / assets $+ 0.847 *$ retained earnings / assets $+$ $3.107 *$ EBIT/assets $+ 0.420 *$ equity/liabilities $+ 0.998 *$ sales/assets. Since banks do not report interest rates on their credit commitments in the CCR data, we use in Table D.5 $\widetilde{R}_{ft}$, a proxy for firm-level interest rates defined as the ratio between interest expenses and outstanding credit. For firms filling the complete model of Annual Accounts, we define interest expenses as debt charges and outstanding credit as the sum of short-term and long-term debt to credit institutions. For firms using the abridged and micro versions, interest expenses are defined as recurring financial charges up to 2015, and as the difference between total financial charges and extraordinary financial from 2016 onward. Outstanding credit for these firms is calculated as the sum of short-term debt to credit institutions and long-term debt to credit institutions, leasing, and other similar obligations. When available, we calculate firm age using the firm's start and cessation dates. Otherwise, we proxy firm age based on the number of consecutive Annual Accounts filed since 1985, leveraging the long time series available.

Finally, retained earnings/assets, EBIT/assets, and sales/assets are trimmed at the 1% and 99% percentiles, while net working capital/assets and equity/liabilities are trimmed at the 1% level.

B Lender-Assessed Default Probabilities

Since 2014, European banking supervision is ensured by the Single Supervisory Mechanism (SSM).[43] It is composed of the ECB and national supervisory authorities and enforces consistent supervisory mechanisms to ensure the stability of the European banking system. The ECB directly supervises 113 *significant institutions* deemed to be of systemic importance for the banking system and leaves the supervision of about 2,000 *less significant institutions* to national supervisory authorities while exerting oversight on them.[44]

[43] The SSM was established by Regulation (EU) No 468/2014 of the European Central Bank of 16 April 2014.

[44] Significant institutions hold about 82% of banking assets in the European banking system (source: ECB). The ECB can classify an institution as significant when its total value of assets exceeds 30 billion, the total value of its assets exceeds 5 billion and the ratio of its cross-border assets/liabilities in more than one other participating Member State to its total assets/liabilities is above 20%, if it has requested or received

While less significant institutions can benefit from looser supervision based on their size and systemic importance, minimum standards ensure consistent supervision across all financial institutions.

Significant institutions can be granted the permission to use internal models to estimate their exposure to credit risks, market risks, and counterparty credit, including borrower-level default probabilities. These risks parameters are then used to set banks own capital requirements. In line with European regulation, banks must adhere to the ECB's guide to internal models so that every institution is subject to similar supervisory practices.[45] To ensure the validity of these internal models and capital requirements, each significant institution is assigned a dedicated Joint Supervisory Team (JST) comprised of a coordinator from the ECB, sub-coordinators from the national supervisor, and a team of experts from the previous two authorities, all of which rotate on a regular basis. These JSTs perform both on-site inspections and investigations of banks' internal models. Any changes to these internal models are subject to regulator approval. Given this institutional context, lender-assessed default probabilities should accurately and consistently capture borrower riskiness.

We perform two validation exercises to ensure the relevance of these default probabilities in the context of bank specialization. First, we verify their forecasting power on realized default by estimating

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

where $\mathbb{1}\{\text{Default}_{bft,t+4}\}$ is an indicator variable equal to one when firm f defaults within the next year, and $Q_q\left\{PD_{bft}\right\}$ is a fixed effect equal to one when $PD_{bft} \in [q, q+1)$, $q = 0, \cdots, 9$. Default probabilities are severely left skewed. To avoid noise, we focus on default probabilities smaller than 10%, which is the case for 90% of observations. Appendix Figure D.1 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's default risk adequately.[46]

direct public financial assistance, or if it is of economic importance for a specific country of the EU economy as a whole.

[45] The guide to internal models was an outcome of the targeted review of internal models (TRIM) project, a large-scale review of banks internal models conducted between 2016 and 2021 to increase the consistency of the implementation of regulatory requirements. The TRIM involved 200 on-site internal model investigations at 65 institutions and covered internal models for credit risk, market risk and counterparty credit risk. Each investigated institution was also assigned a grade.

[46] Note that the exponential shape of the coefficients is the result of the default probabilities being heavily

Second, we test for lender disagreement in their risk assessments across industries of specialization 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 Appendix Figure D.2 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.

C Derivation of the Switching Threshold to a New Relationship

In specification (1), 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 rela-

skewed toward 0, so most deciles are tightly concentrated around low default probabilities.

tionship, 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 $\sigma(RL_{bf}) \approx 6.4$.

D Supplementary Figures and Tables

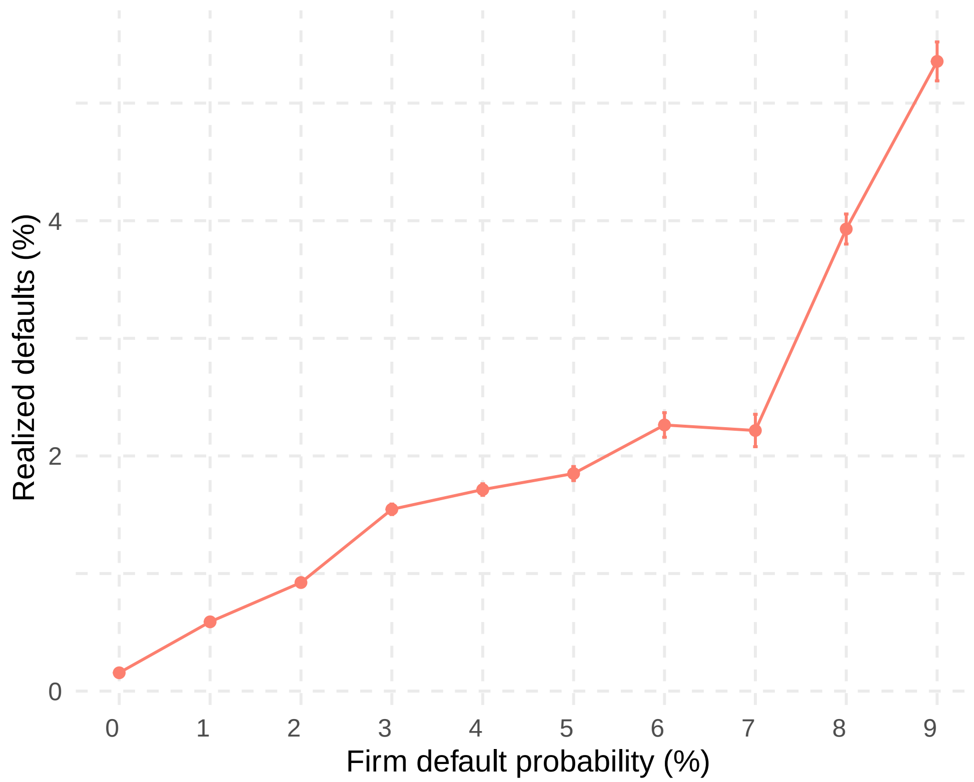

Figure D.1: Assessed Default Probabilities Predict Realized Past Due Payments

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

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

where $\mathbb{1}\{\text{Default}_{bft,t+4}\}$ is an indicator equal to one when firm f has a defaults 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). 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.

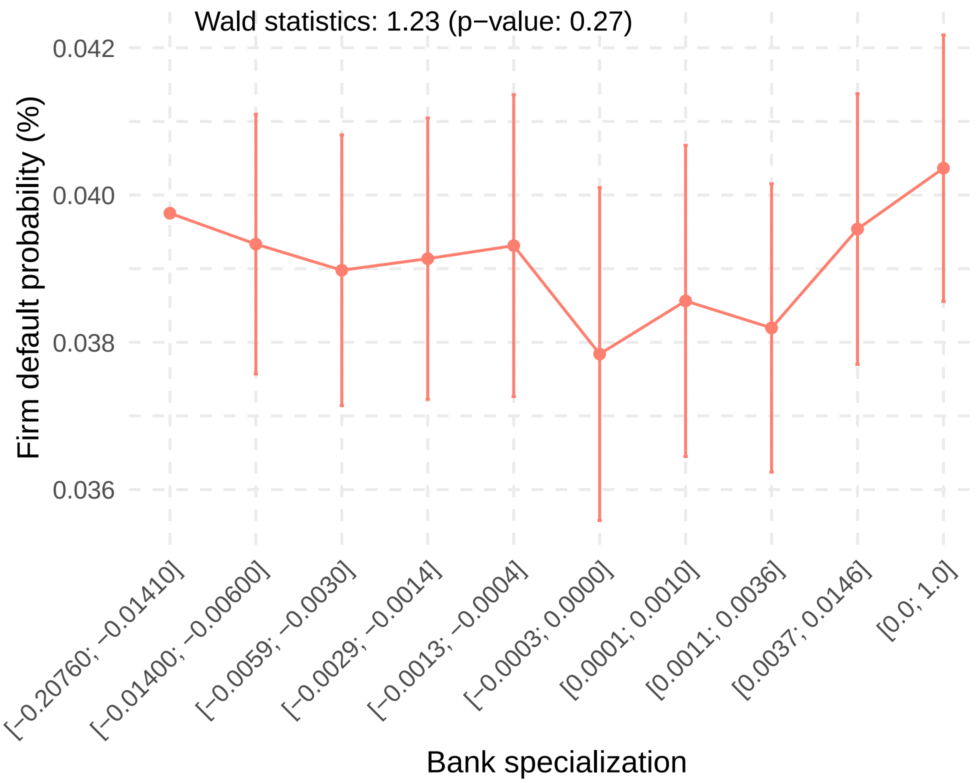

Figure D.2: Banks Assign Similar Default Probabilities Regardless of Specialization

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). 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.

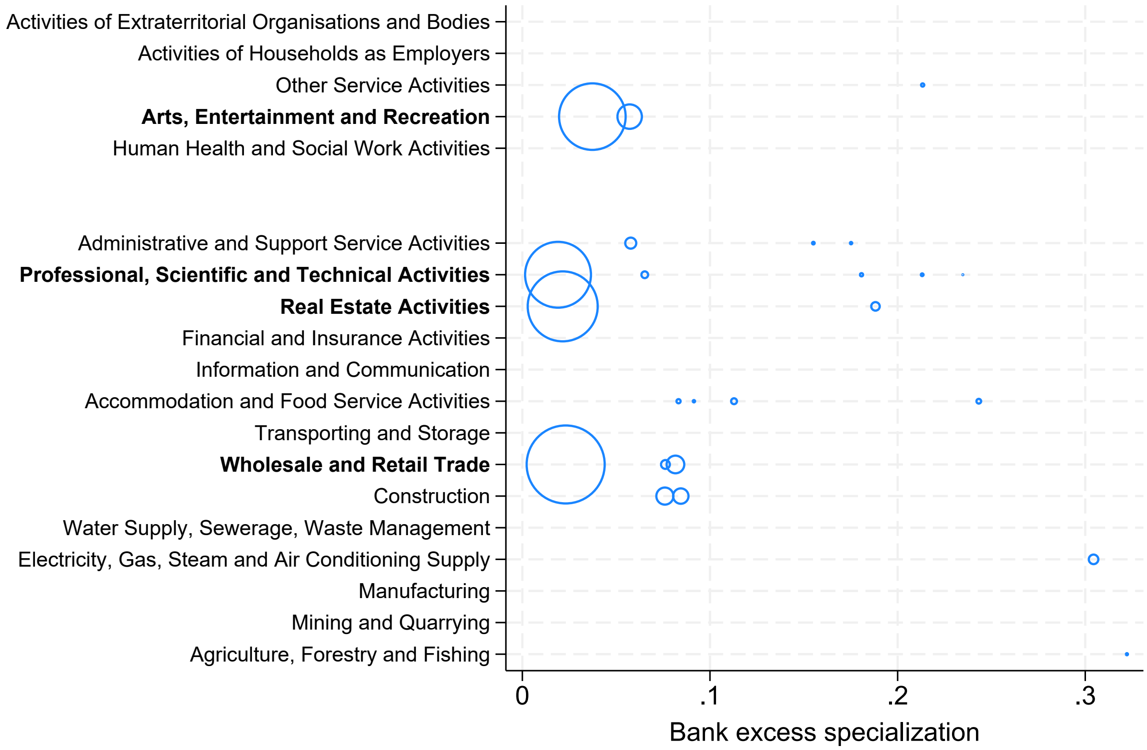

Figure D.3: Banks Most Preferred Industries

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).

Table D.1: Firms Summary Statistics 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 5. See Appendix A for variables construction. Quarterly credit data sourced from the Belgian Corporate Credit Register (cf. Appendix A); 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 D.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 variations of specification (8), where variable definitions are identical to Table 4. 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). Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table D.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 (8), where $Spe_{bs(f)t}$ refers to various measures of bank industry specialization and variable definitions are identical to Table 4. 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. 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). Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table D.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 specification (1), 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. Variable definitions are identical to Table 3. 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). Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

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

Outcome	$\widetilde{R}_{ft}$ (1)	(2)
$\ln(PD_{bft})$		88.1***
		(2.9)
RL_{bft}	109.1***	109.6***
	(3.0)	(3.1)
$\text{Spe}_{bs(f)t}$	-51.6	-54.5
	(33.6)	(34.7)
$\ln(PD_{bft}) \times \text{Spe}_{bs(f)t}$		-40.8**
		(19.2)
$\ln(PD_{bft}) \times RL_{bft}$		-4.9***
		(1.4)
$RL_{bft} \times \text{Spe}_{bs(f)t}$	48.9**	51.5***
	(19.1)	(20.0)
$\ln(PD_{bft}) \times RL_{bft} \times \text{Spe}_{bs(f)t}$		19.7*
		(11.8)
Relationship controls	Yes	Yes
Firm controls	Yes	Yes
Bank-Time FEs	Yes	Yes
Observations	738,204	738,204
Adjusted R^2	0.15	0.15

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

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

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 single-lender bank-firm relationships from the Belgian Corporate Credit Register (CCR) over the period 2012-2021 using term loans and credit lines (cf. Appendix A). Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

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

Outcome	R_{bfct}			
Firm riskiness (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***	5.3***
	(0.73)	(0.20)	(0.23)	(0.30)
RL_{bft}	8.0***	5.0***	4.1***	3.8***
	(0.44)	(0.51)	(0.39)	(0.41)
$\text{Spe}_{bs(f)t}$	-18.2***	-23.3***	-21.7***	-22.7***
	(1.9)	(2.7)	(2.4)	(2.6)
$x_{bft} \times RL_{bft}$	1.4***	-0.37**	-1.2***	-1.3***
	(0.44)	(0.15)	(0.17)	(0.17)
$RL_{bft} \times \text{Spe}_{bs(f)t}$	4.5**	9.3***	6.3***	5.8***
	(2.2)	(2.7)	(2.1)	(2.1)
$x_{bft} \times \text{Spe}_{bs(f)t}$	-12.6***	-3.5***	-4.5***	-5.2***
	(2.7)	(0.79)	(0.91)	(1.1)
$x_{bft} \times RL_{bft} \times \text{Spe}_{bs(f)t}$	7.1***	2.9***	3.4***	2.6***
	(2.7)	(0.86)	(0.97)	(0.93)
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	445,603
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). Other variable definitions are identical to Table 3. 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). Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

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

Outcome	R_{bfct}				
Firm characteristic (x_{ft})	EBIT/A	Sales/A	NWC/A	Cash/A	Z-score
	(1)	(2)	(3)	(4)	(5)
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). Variable definitions are identical to Table 3. 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). Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

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

Outcome	Earn/A (1)	Sales/A (2)	CapEx/A (3)	Cash/A (4)	Equity/A (5)	NWC/A (6)
RL_{bft}	-0.30***	0.06	-0.22***	0.41***	0.26	-1.3***
	(0.06)	(0.15)	(0.03)	(0.07)	(0.17)	(0.18)
$\text{Spe}_{bs(f)t}$	-0.98***	-6.0***	-0.07	-1.4***	-1.0*	-1.9***
	(0.19)	(0.49)	(0.11)	(0.23)	(0.59)	(0.61)
$RL_{bft} \times \text{Spe}_{bs(f)t}$	0.40***	2.0***	0.15***	0.54***	0.69**	1.2***
	(0.10)	(0.27)	(0.05)	(0.13)	(0.34)	(0.35)
Bank-Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,273,777	3,053,670	1,462,242	3,331,508	3,304,164	3,304,206
Adjusted R^2	0.27	0.70	0.16	0.62	0.66	0.65

Notes: Table reports estimated coefficients of interest from specification (7), 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). Standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.