Borrower Technology Similarity and Bank Loan Contracting

Mingze Gao Yunying Huang Steven Ongena* Eliza Wu

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Abstract

Do banks accumulate knowledge about corporate technology, and does it matter for their lending? To answer this question, we combine corporate innovation with syndicated loan data. We find that loans to firms sharing similar technologies with banks' prior borrowers obtain lower loan spreads. We can rule out product market competition, the value of their technology and ability to innovate, and/or numerous other firm characteristics as alternative explanations. By estimating a structural bank-borrower matching model and exploiting the consummation of bank mergers and acquisitions, we can show that shocks to banks' technology knowledge causally affect loan spreads.

Keywords: Technology similarity, Loan contracting, Matching model, Relationship lending

JEL classifications: G21, G32, O33

Mingze Gao: Macquarie Business School, Macquarie University, NSW 2109, Australia; Email: mingze.gao@mq.edu.au. Yunying Huang: University of Sydney Business School, University of Sydney, NSW 2006, Australia; Email: yunying.huang@sydney.edu.au. Steven Ongena: University of Zurich, Swiss Finance Institute, KU Leuven, NTNU Business School and CEPR, Plattenstrasse 14, Zurich 8032, Switzerland; Email: steven.ongena@bf.uzh.ch. Eliza Wu: University of Sydney Business School, University of Sydney, NSW 2006, Australia; Email: eliza.wu@sydney.edu.au. For helpful comments, we thank Olivier De Jonghe, Manasa Gopal, Iftekhar Hasan, Christoph Herpfer, Vasso Ioannidou, Jan Keil, Christoph Schneider, Yu Shan, Jing Yu, Anthony Lee Zhang, conference participants at the European Finance Association 50th Annual Meeting, the Financial Management Association 2023 Annual Meeting, and the 35th Australasian Finance and Banking Conference, and seminar participants at the Macquarie University and the University of Sydney. We would like to acknowledge the research support received from the Australian Research Council (ARC, DP210102611). All errors are our own.

*Corresponding author.

I Introduction

In spite of technological innovations being a key driver of economic growth, the role of borrowers' technology profiles in bank lending decisions remains an open issue. In the U.S., corporations are the main loci for technological innovations, which account for the bulk of R&D expenditures (Chava et al., 2017). The financing of innovative firms is therefore an important function of the financial sector in which banks play a critical role, for example through the syndicated loan market. However, the information asymmetry and adverse selection faced by banks increase the costs in loan screening and monitoring, raising the loan costs to borrowers and the likelihood of under-funding productive firms (Greenwood et al., 2010). The inherently risky high-tech nature of innovative firms exacerbates the under-funding problem due to their high opacity and hence the requirement for specialized expertise to assess credit risk.

To alleviate these funding challenges, greater information disclosure for borrowers is an option (Saidi & Žaldokas, 2021). Alternatively, the bank's accumulated knowledge from past lending to firms sharing similar technologies could imply a source of value via cost savings in loan screening and monitoring. Such an information advantage may rationally lead to a degree of bank specialization in technologies that overrides banks' industry specialization because firms from different industries can share similar technologies. For example, Hyundai Steel Co. (a steel-making company), Deutsche Post Ag (a mail services company), and Berkshire Grey Inc. (a robotics company) all have patents granted in the Cooperative Patent Classification (CPC) class B65G "Transport or Storage Devices".[1]

Given this information advantage, do banks then, cut loan spreads when lending to a borrower who has a high technology similarity with the banks' prior borrowers? If so, is such

[1]CPC is a patent classification system jointly developed by the United States Patent and Trademark Office (USPTO) and European Patent Office (EPO) which has replaced the United States Patent Classification (USPC) in 2013. See our later discussions for more details. The three companies Hyundai Steel Co., Deutsche Post Ag, and Berkshire Grey Inc. have distinct Standard Industrial Classification (SIC) codes 3312, 7389, and 3569, respectively, but all have some patents related to conveyors (group 15 under class B65G).

bank-borrower matching economically optimal for banks, borrowers, or for both?

We rely on borrower patent information to measure, as in Jaffe (1986) and Bloom et al. (2013), the average pair-wise technology similarity between the prospective borrower and its bank's prior borrowers in recent years. While past information accumulation by the bank could lead to a lowering of spreads, the net impact, however, remains ex-ante unclear and warrants an empirical study for two reasons. First, borrowers with similar technologies may face greater product market competition as a result of the technologies being more likely to be applied in related product markets (e.g., Bereskin et al., 2022). A high technology similarity between the bank's current and past borrowers could also imply more industry segment concentration in the bank's loan portfolio, undermining potential diversification benefits (e.g. Diamond, 1984; Boyd & Prescott, 1986).[2] Second, banks may extract rents based on their accumulated information advantage (e.g., Rajan, 1992) instead of passing on to the borrower the cost savings from the reduced due diligence needed in assessing the borrower's technology profile. These possible channels could lead to a positive relationship between technology similarity and loan spreads, but are not supported by our empirical results. We find that increased industry segment concentration is positively associated with the loan spread, but a higher borrower technology similarity causally reduces the loan spread. Further, we show that lower spreads of loans to borrowers with a high technology similarity to the banks' prior borrowers are economically optimal, enhancing the total economic surplus for both banks and borrowers. We establish this finding using a structural bank-borrower matching model similar to Fox (2017, 2018) and Schwert (2018).

Specifically, at each loan's origination, we compute the technology similarity of the borrower and its bank's prior borrowers in the past five years using the average pair-wise technology similarity measure from Jaffe (1986) and Bloom et al. (2013). The pair-wise technology similarity is a cosine similarity of the firm's technology profiles measured by the proportions of patents granted in each of the Cooperative Patent Classification (CPC) technology classes.

[2] The technology similarity of a prospective borrower and the bank's prior borrowers is positively correlated with their industry segment similarity with a correlation coefficient of 0.21 in our sample.

In this application our technology similarity measure does differ somewhat from the technology spillover measure deployed in Bloom et al. (2013) and Qiu and Wan (2015). These prior studies captured the firm-year technology similarity to the whole economy. Instead, our bank-firm-year level technology similarity measure represents a bank's time-varying technological expertise specific to each borrower.

Using a comprehensive sample of U.S. syndicated loans from January 1990 to December 2020, we show that loans to firms with a higher technology similarity with banks' prior borrowers have lower loan spreads and total costs. A one-standard-deviation increase in technology similarity is associated with approximately a 4 basis points (bps) reduction in loan spreads. This reduction is economically meaningful for a mean loan spread of 205 bps (175 bps), being equivalent to an annual loan cost saving of \$170,000 (\$66,000) for a mean (median) loan of \$425.14 (166) million in our sample.[3] Such effect remains even after controlling for borrower's product market rivalry (Hoberg et al., 2014; Hoberg & Phillips, 2016), product market segment similarity (Bloom et al., 2013; Bereskin et al., 2022), prior lending relationship (Bharath et al., 2011), and borrower's patent stock and value (Chava et al., 2017; Kogan et al., 2017). Innovative borrowers such as green firms may take this opportunity to reduce their financing costs, which have been shown to receive favorable loan recommendations from bankers (Bu et al., 2023).

In robustness tests, we rule out the possibility that bank industry specialization drives our results by controlling for lender times industry times year fixed effects. We show that our results are also robust to alternative industry classifications, alternative window sizes used for measuring firm patent classes, as well as alternative constructs of borrower technology similarity addressing potential attenuation bias. Further, even when we exclude firms without patents, loans originated by banks with few recent borrowers, or loans to major

[3]We find that loan size, maturity, and secured status for example are not affected by technology similarity, possibly because these loan characteristics are more driven by corporate needs and assets, and are thereby predetermined. Hence, the bad control problem that may exist when including these loan terms as independent variables may be less acute; yet, we confirm that their exclusion leaves the main estimates we report mostly unaltered.

customers, we find the same inference. We additionally conduct a placebo test and find no relationship between loan spreads and the technology similarity of a borrowing firm with the bank's future borrowers.

We then show that technology similarity is indeed informative about borrower's creditworthiness in both contemporaneous and predictive regressions. A higher technology similarity with prior borrowers is negatively associated with the absolute difference between their credit risks measured by the Altman's Z-score, Merton (1974) default probability, and their debt service capabilities measured by profitability and cash holding. These results suggest that firms with similar technologies tend to have similar credit risks both at and post loan origination, which could lower banks' screening and monitoring costs, leading to reduced loan spreads.

However, establishing a causal link between a borrower's technology similarity with its bank's prior borrowers and loan spreads is empirically challenging. Given that our technology similarity measure is specific to each bank-borrower matched pair (at loan origination), it is difficult to find an exogenous shock directly to the technology similarity measure, which alters the borrower's technology profile but does not affect the bank-borrower matching or the borrower's fundamentals and future business prospects. An instrumental variable regression approach is also precluded as an instrumental variable that correlates with technology similarity but not with borrower characteristics used in bank loan pricing is hard to come by. To the best of our knowledge, prior studies such as Lee et al. (2019), McLemore et al. (2021), and Bereskin et al. (2022) also encounter similar identification issues. We therefore explore two alternative methods to address the identification challenges. We start with a structural model that shows such bank-borrower matching is economically optimal, followed by difference-in-differences estimations exploiting exogenous shifts to the stock of banks' accumulated technological knowledge using bank mergers.

First and foremost, we estimate a structural matching model similar to Fox (2017, 2018) and Schwert (2018) which allows us to identify drivers of bank-borrower matching assignments in the absence of unobservable non-matching assignments.[4] We show that such technology similarity is a major determinant of bank's lending decision and the observed loans are endogenously a result of simultaneous value maximization for banks and borrowers. Specifically, both banks and firms in our model maximize their respective value. A loan contract contains transfer payments (e.g., interests and fees). Because we do not have data on the unobservable counterfactual loans, we derive an inequality condition for simultaneous value maximization without the transfer payment component. Assuming that observed actual bank-borrower matches (i.e., loans) yield higher value than unobservable counterfactual loans, we perform a semi-parametric estimation for the loan determinants at the bank-borrower level (Schwert, 2018). Our results suggest that the total economic surplus for banks and borrowers can be enhanced by matching banks to borrowers whose technology profiles are similar to that of the banks' prior borrowers. Lower loan spreads for borrowers sharing similar technology profiles with the banks' prior borrowers are economically optimal for both banks and borrowers.

To complement the matching model, we further use difference-in-differences (DiD) estimations. While it is challenging to find an exogenous shock to borrower technology similarity, we alternatively exploit reasonably exogenous shifts to the stock of banks' accumulated technological knowledge using bank mergers and acquisitions (M&As), which increase acquirer banks' technology knowledge but do not affect their *extant* borrowers' creditworthiness. Using stacked cohorts of treated banks with M&A activities and control banks matched via propensity scores that have no M&A activities in the five-year window around the M&A event year, we find that loans extended to extant borrowers by acquirer banks after the M&A event are significantly cheaper than loans issued before, as compared to the loans originated by control banks.

Additionally, we show that the documented beneficial effect of borrower technology similarity on loan spreads is stronger for loans originated by smaller, less-capitalized, or less-liquid

[4] We can observe only the loans that have been originated, not the potential loans that could have been originated if borrowers chose different lenders.

banks, and for good borrowers with lower credit risk, leverage, or higher profitability. These results are consistent with our conjecture that smaller, less-capitalized, or less-liquid banks have more limited resources to screen and monitor borrowers and hence may place higher value on their accumulated technology knowledge from past lending. Banks are also more willing to cut loan spreads for high-quality borrowers with lower credit risk, lower leverage, or higher profitability, and for the borrowers of low technological obsolescence.

This study contributes to the literature in four directions. Firstly, we contribute to the burgeoning literature on the implications of technological innovation (e.g., He & Tian, 2020). For example, recent studies identify the impact of technology spillover on product market rivalry (Bloom et al., 2013), cash holdings (Qiu & Wan, 2015), technology styles (Byun et al., 2021) and innovation outputs (Matray, 2021). We extend the technology measures developed by Hall et al. (2001), Bloom et al. (2013), and Kogan et al. (2017) in the context of bank lending by proposing a measure of a bank's time-varying technological expertise specific to each borrower. We also shed new light on the economic value of firms' technological innovation in financing decisions.

Secondly, we contribute to the literature on the interplay between financial intermediaries and firm technological innovation. On the one hand, many extant studies investigate how the banking industry affects firm innovation outputs (e.g., Chava et al., 2013; Cornaggia et al., 2015). On the other hand, Chava et al. (2017) find that firms with more innovation outputs receive cheaper bank loans. Saidi and Žaldokas (2021) find that enhanced technology disclosure improves banking competition and helps reduce loan costs for borrowers. We extend the work of Mann (2018) on the intangible and collateral value of firms' technology profiles by showing that the similarity across different borrowers' technology profiles is informative for credit risk assessment.

Thirdly, our study contributes to the bank loan contracting and relationship lending literature. We highlight the value of accumulated technology knowledge from banks' past lending, thereby extending the literature on relationship lending (e.g. Demiroglu & James, 2010; Ioannidou & Ongena, 2010; Bharath et al., 2011; Murfin, 2012). Our study provides further evidence for the crucial role of information asymmetry on bank loan contracting (e.g. Sufi, 2007; Ivashina, 2009; Demiroglu et al., 2021; Gustafson et al., 2021), and sheds new light on the relation between bank's private information advantage and rent extraction (e.g. Schenone, 2010).

Finally, our study extends the prior literature on various alternative determinants of bank loan contracting (e.g. Hasan et al., 2014; Campello & Gao, 2017; Carvalho et al., 2022) by showing that bank loan costs are dependent on the shared technological knowledge across banks' borrowers. Our study also contributes to the literature on bank lending specialization. For example, Giometti and Pietrosanti (2022) show that bank specialization in borrower industries leads to laxer contract terms for borrowers in the industry. Gopal (2021) shows that banks increase credit supply to borrowers whose collateral they have specialization in. Beck et al. (2022) show that bank specialization reduce both individual and systemic bank risk. We document that banks' accumulated technology knowledge reduces loan costs and that matching borrowers to banks with a clear specialization in the borrower's technology increases total economic surplus.

Our findings also have significant policy implications, particularly for the financing of innovative technologies. The green transition is clearly a juncture in time when innovative technology is urgently needed but is not yet very familiar to banks. Due to the high information asymmetry involved, banks may be hesitant to finance technologies they have not previously encountered, leading to an under-funding problem (Greenwood et al., 2010). To address this, government support may be introduced to encourage bank financing for technological innovation by, for example, subsidizing initial loans. As banks gain experience and knowledge, loan rates are likely to decrease, allowing for the phasing out of government subsidies. This approach, akin to policies aimed at small business financing, could be particularly beneficial for new technology adoption.

The rest of the paper proceeds as follows. Section II develops the hypotheses. Section III discusses our data and key measurements. Section IV presents our baseline results. Section V discusses the identification challenges and investigates the economic mechanisms. Section VI presents some additional results. Section VII concludes.

II Hypothesis development

Information asymmetry between banks and borrowing firms plays a major role in bank loan contracting (e.g., Sufi, 2007; Ivashina, 2009). Banks invest substantial resources in loan screening and monitoring to collect and assess information relevant to prospective borrowers' creditworthiness (e.g., Sufi, 2007; Agarwal & Hauswald, 2010; Schenone, 2010; Rajan et al., 2015; Botsch & Vanasco, 2019; Gustafson et al., 2021). Beyond the borrowing firm's fundamental financial metrics such as leverage, profitability, and so on, non-financial firm characteristics have also been receiving increased attention. One strand of banking literature, for example, focuses on intangible capital, including technology capital, and its impact on bank loan contracting (e.g. Hollander & Verriest, 2016; Hasan et al., 2017; Agarwal & Ben-David, 2018; Karolyi, 2018). Specifically, firm technology capital is related to its cash holding (Qiu & Wan, 2015), governance structure (Frydman & Papanikolaou, 2018), creditworthiness (Dannhauser, 2017), competitive scope and long-term growth (e.g. Romer, 1990; Glasso & Schankerman, 2013). Chava et al. (2017) find that an exogenous enhancement of intellectual property protection and patent value results in lower bank loan costs. Mann (2018) identifies that improved pledgeability of patents contributes to the use of debt financing. Saidi and Žaldokas (2021) show that increased information disclosure on borrowers' technology profiles reduces the cost of switching lenders and results in a more competitive loan market and lowers the cost of bank financing.

However, firm technology capital is inherently difficult to evaluate due to its opacity and limited redeployability, exhibiting higher knowledge barriers compared to fundamental or other soft information sources (e.g., Hall & Lerner, 2010; He & Tian, 2013). Therefore, the accumulated knowledge from banks' prior experience in lending to firms with certain technology profiles is arguably valuable and relevant for future bank financing. To the extent that such accumulated technology knowledge reduces adverse selection and information asymmetry, we expect that banks are more likely to lend to borrowers sharing similar technologies with the banks' prior borrowers and they pass on the cost savings from reduced screening and monitoring to their borrowers (Bharath et al., 2011). We therefore develop our Hypothesis 1 as follows:

Hypothesis 1 *Banks charge lower loan spreads for borrowing firms with a higher technology similarity with the banks' prior borrowers.*

Nevertheless, we acknowledge that Hypothesis 1 is not clear-cut for two reasons. First, borrowers sharing similar technology profiles may face greater product market competition, which is known to cause higher bank loan costs (e.g., Valta, 2012). It could also imply an increased industry concentration of bank loan portfolios as borrowers sharing similar technologies are likely to compete in the same or related industries, undermining the potential diversification benefits to the bank. Second, banks may use their information advantage to extract rents (Rajan, 1992), since the borrowing firm could face worse outside options as it represents greater information asymmetry to other lenders who have less experience in lending to firms with similar technologies. Therefore, it remains an empirical question whether a borrower with a higher technology similarity as the bank's prior borrowers receives lower loan spreads.

Additionally, we consider the role of technology similarity from both the bank and borrower sides. For banks, because the accumulated technology knowledge reduces the expensive resources required for evaluating borrower technology profiles, we conjecture that more constrained banks are likely to benefit more from such accumulated knowledge. Specifically, we expect that smaller banks with less technology expertise would value borrower technology similarity relatively more. Similarly, less-capitalized banks may be more risk-averse and value more the certainty from borrowers of higher technology similarity to their prior borrowers.

Less-liquid banks are likewise more constrained by their resources and may thus value more the cost savings from the accumulated technology knowledge. As Gustafson et al. (2021) show that the value of information obtained is negatively related to loan spreads, we expect that smaller, less-capitalized, or less-liquid banks are likely more willing to reduce loan spreads for borrowers coming with a higher technology similarity to their existing borrowers as this allows banks to capitalize more on their accumulated knowledge. It is possible, however, that more constrained banks do not pass on the cost savings to borrowers. The banks may trade off the short-term gains from retaining the surplus and the potential losses due to their customer switching banks. Given that less-bank-dependent firms (e.g., with bond market access) are more likely to borrow from less-capitalized banks (Schwert, 2018), we expect that the more constrained banks, due to concerns of customer retention, will charge lower loan spreads when borrowing firms have a higher technology similarity with their prior borrowers. We thus have the following second hypothesis:

Hypothesis 2 *Smaller, less-capitalized, or less-liquid banks charge lower loan spreads for borrowing firms that share similar technologies with the banks' prior borrowers.*

From a borrower's perspective, we expect the borrowers with lower credit risk, lower leverage and higher profitability to receive lower loan spreads from banks when they have a higher technology similarity with the banks' prior borrowers. These borrowers have better capabilities in servicing debt, to whom banks may be more willing to pass on the cost savings due to the reduced due diligence needed. This helps with retaining and attracting good-quality borrowers. On the other hand, while banks' accumulated technological knowledge is arguably valuable when screening lower-quality borrowers with higher risks, it is ambiguous whether the cost savings due to such knowledge will be passed on to these borrowers more than to the higher-quality borrowers. If more risky firms receive greater benefits when borrowing from banks whose prior borrowers share similar technologies, an adverse selection problem seems imminent.

Moreover, the importance of banks' technological expertise increases when borrowers' technologies are cutting-edge and up-to-date. More advanced technologies are typically harder to fully comprehend and of higher value, demanding greater screening efforts from lenders. In this case, banks' knowledge of the borrower's technology plays a more important role in reducing due diligence costs and hence leads to relatively lower loan spreads. Firms with a high technological obsolescence are shown to have lower growth and productivity (Ma, 2021), and as a result may not receive reduced loan costs when borrowing even if they share similar technologies with banks' prior borrowers. Therefore, we form our third and fourth hypotheses as below:

Hypothesis 3 *Banks charge lower loan spreads for less risky, less levered, and more profitable borrowers that share similar technologies with the banks' prior borrowers.*

Hypothesis 4 *Banks charge lower loan spreads for borrowers that share similar technologies with the banks' prior borrowers when borrowers have lower levels of technological obsolescence.*

III Sample and variable construction

A Measuring technology similarity

To capture banks' time-varying knowledge of borrowers' technology profiles, we require a measure that varies by bank-firm pair and over time. Therefore, we use the technology similarity of a borrower with the bank's recent borrowers to gauge the bank's knowledge of this particular borrower's technology profile at loan origination. Because this technology similarity measure is computed for each loan, it is naturally specific to the pair of bank and borrower at loan origination and offers some important features. It allows for not only a bank having different levels of knowledge in different technology classes at a given time, but also a bank with time-varying knowledge in a given technology class. Specifically, we compute the technology similarity measure in two steps. First, at each loan's origination, we compute the pairwise technology similarity between the borrower and each of the bank's recent borrowers. Second, we aggregate the pairwise similarities to the bank-borrower level as our measure of the bank's knowledge of the borrower's technology at the time of loan origination.

In the first step, we compute the pairwise technology similarity, consistent with Jaffe (1986), as the spatial proximity of two firms' technology profiles measured by patents granted and their technology classifications. Using this method, for example, Bloom et al. (2013), Qiu and Wan (2015), and Byun et al. (2021) obtain the technology similarity between each firm and the whole economy to measure technology spillover. Lee et al. (2019) and McLemore et al. (2021) sum over the technology similarity within pre-specified firm sets to measure the technology linkage between firms. Empirically, we collect all firms' patents granted and their technology classifications using the Cooperative Patent Classification (CPC), a classification system jointly developed by the United States Patent and Trademark Office (USPTO) and European Patent Office (EPO).[5] The pairwise technology similarity between a borrowing firm i and a bank's prior borrower j, as at the origination time t, is the normalized uncentered cosine similarity between the patent portfolio of firm i at time t and the portfolio of firm j at its prior borrowing time τ:

$$Pairwise\ Technology\ Similarity_{ijt\tau} = \frac{(\boldsymbol{T_{it}T'_{j\tau}})}{(\boldsymbol{T_{it}T'_{it}})^{0.5}(\boldsymbol{T_{j\tau}T'_{j\tau}})^{0.5}} \tag{1}$$

where T_{it} is a k-dimensional vector of firm i's proportions of patents granted in each of the k technology classes over the past five years,[6] where the value of each element in T_{it} is strictly between zero and one. We assume that a bank learns the most about a borrower's technology profile at loan origination, and hence we use the patent portfolio of prior borrowers at their

[5]In the later section of data sources we explain in detail the technology classifications.

[6]The total number of technology classifications, k, varies with time. We use a k of 660. We follow the standard innovation literature to use a five-year window to allow for some accumulation of technology stock (e.g. Bloom et al., 2013; Lee et al., 2019). Our results are robust to alternative window sizes such as 1-year, 3-year, 7-year and all-history windows as shown in Table A2. All of our empirical results still hold if we use the USPTO classification system using data before 2013 (the USPTO technology class system was replaced by the newer CPC technology class system in 2013).

respective borrowing time τ in the five-year window, i.e., $\tau \in [t-5, t-1]$, instead of time t, in computing the pairwise technology similarity. Figure 1 provides a graphical illustration.

[Insert Figure 1 about here]

In the second step, our key variable of interest, the technology similarity between the borrower firm i and the bank b's recent borrowers is the average pairwise similarity:[7]

$$\textit{Technology Similarity}_{ibt} = \frac{1}{N}\sum_{j=1}^{N} \textit{Pairwise Technology Similarity}_{ijt\tau} \tag{2}$$

where N is the total number of the loans that bank b serves as the lead bank in the five-years leading up to time t. Note that we do not exclude the borrowing firm from the sample of the bank's recent borrowers because a firm's technology profile varies over time, i.e., we allow T_{it} and $T_{j\tau}$ in Equation 1 to represent the patent portfolio of the same firm at different times. To a certain extent, this could cause a mechanical correlation between technology similarity and relationship lending should the firm's technology profile be stable over time. However, there are two reasons why it is less of a concern. First, the technology profile of a firm changes as measured by recently granted patents, and lending banks still face increased screening and monitoring costs should the same borrower experience a drastic change in its technology profile. Second, our technology similarity measure is averaged across all pairs of recent borrowers and the focal firm. As long as the bank lends to more than one firm in the past five years, the concern of a mechanical correlation between technology similarity and relationship lending due to the inclusion of the focal firm in the group of recent borrowers is mitigated.[8]

Our technology similarity measure differs from the well-known technology spillover measure (Bloom et al., 2013; Qiu & Wan, 2015) which captures a firm's technology similarity

[7] All our results are robust to the alternative use of technology similarity weighted by loan amount.

[8] Further, we control for past lending relationships, following the relationship lending literature (Bharath et al., 2011), in our regression analysis. Our results are robust to the use of a 3-year or 5-year relationship window and to alternative relationship strength measures based on the prior number of loans or total loan amount.

to the whole economy. Our measure also differs from firm-level technological obsolescence measure by Ma (2021) based on patent citations. While a firm may have highly-valued frontier technologies, they are not necessary familiar to the bank. As discussed earlier, we calculate a borrower technology similarity measure specific to each bank-borrower pair at loan origination to capture each bank's time-varying technological expertise on a specific borrower. In the later section of robustness tests, we present and discuss alternative constructs of technology similarity measure.

B Sample and summary statistics

B.1 Data sources

We collect the patent data from the United States Patent and Trademark Office (USPTO) for the period from 1985 to 2020. We use a five-year window for computing technology similarity. To match patent assignee names to Compustat firms, we rely on the Kogan et al. (2017) (KPSS) linking map. We further cross-check the linkage using other mappings such as Stoffman et al. (2020).[9] Our final sample of patents matched with the Center for Research in Security Prices (CRSP)/Compustat firms consists of 2,331,801 unique observations. Notably, we use the patent grant date when identifying a firm's patent portfolio.[10] We obtain patents' technology class classification data directly from the USPTO PatentsView, which regularly updates patent information including classifications, inventors, and organizations.[11] Prior

[9] Several firm-patent mapping tables are available. For example, the National Bureau of Economic Research (NBER) patent database by Hall et al. (2001) is used in He and Tian (2013) and Tian and Wang (2014), but ends in 2005. Kogan et al. (2017) (KPSS) provide an updated mapping table to 2020, which is another well-known concordance file. Stoffman et al. (2020) (SWY) publish a similar linkage dataset updated to 2020. Given the challenge of fuzzy matching patent assignee names and firm names, we rely on the KPSS dataset primarily and use SWY as a cross-validation and to fill missing mappings wherever possible to ensure maximum accuracy.

[10] The American Inventor Protection Act (AIPA) enacted in 1999 mandates that patent information becomes public at either grant date or 18 months after the patent application date, which significantly affects the banking relationship of innovative firms (Saidi & Žaldokas, 2021). Nevertheless, Lee et al. (2019) argue that a significant proportion of patents might eventually fail to be issued, resulting in actually no innovation outputs for firms. Lee et al. (2019) suggest that using patent grant date would be a conservative choice to assess firm technology profiles.

[11] See, https://www.uspto.gov/ip-policy/economic-research/patentsview.

studies have relied on the United States Patent Classification (USPC) made available by the USPTO (e.g., Bloom et al., 2013; Hsu et al., 2014; Qiu & Wan, 2015; Lee et al., 2019; Byun et al., 2021). However, since the USPTO officially moved to the Cooperative Patent Classification (CPC) system on January 1, 2013, most studies are based on limited sample periods up to 2012. We use the CPC classification to incorporate more recent patent information enabling the expanded identification of 660 technology classes.[12]

Our bank loan sample is sourced from the Thomson Reuters Loan Pricing Corporation (LPC) DealScan database for the same sample period. Specifically, we include all U.S. dollar-denominated loan facilities to U.S. borrowers that can be linked to Compustat using the DealScan-Compustat link table by Chava and Roberts (2008). We use Schwert (2018)'s updated DealScan lender link table to obtain the lender's Compustat identification. We remove utility and financial firms and loans with missing observations on all-in-drawn spread, loan maturity, loan amount, and other necessary loan information. Following Ivashina (2009), a bank in the loan syndicate is classified as the lead bank if it is the administrative agent (if defined), or if it acts as the agent, arranger, bookrunner, lead arranger, lead bank, or lead manager. If a loan has multiple lead banks identified, we assign the one with the highest technology similarity as the lead bank.[13] We collect borrower firms' financial information from Compustat, industry-specific sales data from Compustat Segment, and market data from CRSP. We obtain lender banks' information from Compustat Bank.

B.2 Summary statistics

Our final sample consists of 36,166 loan facilities originated by 110 bank holding companies (banks, hereafter) identified by Compustat Bank to 5,522 distinct firms from 1990

[12] We identify 660 technology classes similar to McLemore et al. (2021) who identify 642 technology classes. The difference is due to new classifications added by the CPC over time, which does not have any material impact on the technology similarity measure.

[13] Bharath et al. (2011) use a similar approach. In studying the lending relationship and loan contract terms, they choose from the multiple lead banks the one that yields the strongest lending relationship with the borrower and assign it to the loan.

to 2020.[14] Given that technology similarity may correlate with product market competition, we control for borrowers' product market rivalry measured by Hoberg et al. (2014) and Hoberg and Phillips (2016). Additionally, we control for product market similarity using a segment similarity measure as in Bloom et al. (2013) and Bereskin et al. (2022), defined as $\frac{1}{N}\sum_{j=1}^{N}\frac{(\boldsymbol{S_{it}S'_{j\tau}})}{(\boldsymbol{S_{it}S'_{it}})^{0.5}(\boldsymbol{S_{j\tau}S'_{j\tau}})^{0.5}}$, where S_{it} is the vector of firm i's proportions of sales in each industry segment and other symbols follow previous notations in Equation 1. To an extent, this segment similarity measure also captures the contribution of the borrower to the bank's loan portfolio industry segment concentration. For other borrower characteristics, we include borrower size, leverage, cash holding, profitability, market-to-book ratio, Altman Z-score, and a dummy variable for whether the borrower has a credit rating (e.g. Bharath et al., 2011; Hasan et al., 2014; Carvalho et al., 2022). We control for the relationship lending as in Bharath et al. (2011). For bank loan characteristics, we include the loan size, maturity, and a dummy variable for whether the loan is secured. The merged sample requires all firm, loan, and bank characteristics to be non-missing. Table 1 reports the summary statistics. Definitions of the variables and data sources are provided in Table A1 in the Appendix. We winsorize all continuous variables used in the analyses by year at the 1st and 99th percentiles.

[Insert Table 1 about here]

Table 1 reports the summary statistics of our sample. Our key variable, technology similarity, ranges from 0 to 1 by construction, with a value of 0 indicating no similarity and 1 the same technology profile. The technology similarity in our sample has a mean of 3.9% and a standard deviation of 6%, with a skewed distribution due to most borrowers sharing no similar technologies. The distribution statistics of our technology similarity measure are comparable to Bereskin et al. (2022), who document a mean of 4.3% and a standard deviation of 11% using a firm-by-firm pairwise sample. The segment similarity variable

[14] We aggregate 533 unique lenders from DealScan to 110 bank holding companies. The DealScan database starts from 1984. We restrict our sample period to match the product market competition data from Hoberg et al. (2014) and Hoberg and Phillips (2016). Nevertheless, our results are robust if our sample starts from 1984, removing Hoberg and Phillips (2016) product market competition measures.

exhibits a relatively similar distribution to technology similarity with a mean (median) of 6.3% (5.2%). This is consistent with prior studies documenting that the scale of technology similarity and segment similarity should be consistent (Bloom et al., 2013).

The key dependent variable is the cost of bank loans measured by the all-in-drawn loan spreads. The mean (median) of loan spreads is 205.31 bps. The average (median) loan size is $425.14 (166) million U.S. dollars. The average (median) maturity is 48.19 (60.00) months. The loan characteristics are consistent with prior literature (e.g. Hasan et al., 2014; Hollander & Verriest, 2016; Campello & Gao, 2017; Carvalho et al., 2022). For example, Campello and Gao (2017) reports average (median) loan spreads of 179.16 (175.00) bps and average (median) loan maturity of 46 (48) months. Hasan et al. (2014) reports average (median) loan spreads of 167 (150) bps and average (median) loan size $487 (150) million U.S. dollars.

In terms of borrower characteristics, the summary statistics show that we have selected a comparable sample of borrowers to those examined in the literature. For example, the average borrower firm has a book value of total assets of $6.566 billion dollars in our sample. The average (median) natural logarithm of the total asset size of borrowers in our sample is 7.074 (7.101), and the average (median) leverage ratio is 0.314 (0.297). Similarly, Carvalho et al. (2022) reports the mean (median) borrower size of 8.04 (7.99) and the mean (median) borrower leverage of 0.37 (0.32). For bank characteristics, an average bank in our sample has a size of 13.159, a capital ratio of 0.113, a Tier 1 capital ratio of 9.921, and a loan-to-deposit shortfall of -0.115, comparable to previous studies (e.g. Acharya & Mora, 2015; Schwert, 2018).

IV Main results

A Baseline model and results

Our first hypothesis postulates that banks charge lower loan spreads for borrowing firms with a higher technology similarity with the banks' prior borrowers due to cost savings from accumulated technology knowledge. To empirically test whether bank's technology knowledge of a borrower, measured by the borrowers' technology similarity with the bank's prior borrowers at loan origination, reduces loan costs, we start by estimating the following baseline regression:

$$\begin{aligned} \ln(\mathit{Loan\ Spread}_{i,l,t}) = \beta_1 \mathit{Technology\ Similarity}_{i,l,t} + \beta_2 X_{i,t-1} + \beta_3 \Gamma_{l,t} \\ + \text{Fixed Effects} + \varepsilon_{i,l,t} \end{aligned} \tag{3}$$

where $\mathit{Loan\ Spread}_{i,l,t}$ is the all-in-drawn spread of loan l for the firm i at year t. $X_{i,t-1}$ represents the vector of borrower firm characteristics as at year $t-1$ and $\Gamma_{l,t}$ the vector of loan characteristics. Specifically, for borrower characteristics, we control for firm size, leverage, credit risk measured by the Altman Z-score, profitability, market-to-book ratio, cash holding, and whether the borrower has received a credit rating. For loan characteristics, we control for loan size, maturity, and whether it is secured. We control for the bank-borrower prior lending relationships following (Bharath et al., 2011), as relationship lending can also reduce the screening and monitoring costs and hence lower loan spreads. We include borrower industry times year fixed effects to capture unobservable time-varying borrower industry heterogeneity, given that technology innovation and adoption could pertain to industry sectors and possibly cluster by time.[15] Additionally, we control for bank fixed effects, loan type fixed effects, and loan purpose fixed effects. Heteroskedasticity-robust standard errors are clustered by borrower firm.[16]

[15]We use the two-digit SIC codes to identify borrower industry and our results are robust to the use of alternative industry classifications such as four-digit SIC codes.

[16]Alternatively, our results are robust to clustering standard errors by bank or by borrower industry.

[Insert Table 2 about here]

Table 2 presents the results for our baseline model. Consistent with our Hypothesis 1, we find that loans to borrowers with a higher technology similarity with the bank's prior borrowers have lower spreads. Specifically, column (1) shows that our borrower technology similarity measure is negatively associated with loan spreads and is statistically significant at the 1% level. A one-standard-deviation increase in the borrower technology similarity reduces the loan spread by 4 bps.[17] Economically, given a sample mean loan size of $425 million, it translates to a sizable annual loan cost saving of $170,000.

Next, we perform several robustness checks and report results in columns (2) to (8) of Table 2. Our first check concerns the concentration of the bank's loan portfolio. Given that firms sharing similar technologies may operate in similar industry segments, we control for the segment similarity of the borrower and the bank's prior borrowers in column (2). A higher segment similarity indicates a larger overlap of the business lines of the borrowing firm and the bank's existing borrowers. This may capture the bank's industry specialization to some extent, but primarily implies potentially higher industry concentration for the bank's loan portfolio. We empirically find that such higher portfolio concentration is positively associated with loan spreads. The negative relationship between borrower technology similarity and loan spreads, however, remains statistically significant at the 1% level after controlling for segment similarity.

Second, firms sharing similar technologies may lead to greater product market competition, which is expected to cause larger loan spreads (see, e.g. Campello & Gao, 2017; Hasan et al., 2020; Croci et al., 2021; Hasan et al., 2021).[18] To account for such a possibility, we control for borrower product market rivalry using three different measures from Hoberg and

[17]The borrower technology similarity has a sample standard deviation of 0.06 and an estimated coefficient of -0.38 in our baseline model. Since the sample mean value of the natural logarithm of loan spread is 5.066, the reduction in loan spread is $e^{5.066} - e^{5.066-0.38\times0.06} \approx 4$ bps.

[18]However, we note that a higher technology similarity between two firms does not necessarily imply stronger direct competition. More importantly, even if technology similarity results in increased market competition, we should expect that the borrower firm faces higher bank loan costs. Therefore, it can only lead to bias against us finding a negative association between technology similarity and loan spreads.

Phillips (2016) and report results in columns (3) to (5) in Table 2. We find that, as expected, a higher product market HHI indicating less competition is negatively related to borrower loan spreads, and a larger product market similarity or fluidity is positively related to loan spreads. In all cases, borrower technology similarity remains negatively and significantly associated with loan spreads with similar-sized coefficient estimates as the baseline.

Third, we consider the effect of borrower technology value on loan spreads. A borrower with higher technology value may receive favorable loan spreads regardless of its technology similarity with bank's prior borrowers. If technology similarity is then correlated with the firm's technology value,[19] our baseline model would suffer from omitted variable bias. As such, in columns (6) to (8) of Table 2, we control for the borrower's patent value and patent stock, as well as segment similarity and the three product market competition proxies, respectively. We find that in these most conservative specifications, our baseline result on the negative association between borrower technology similarity and loan spreads remains qualitatively unchanged. The robust effect of technology similarity in reducing loan costs suggests that technology similarity contains information beyond bank loan portfolio concentration, borrower firm competition, and technology value.[20]

B Additional robustness and placebo tests

B.1 Bank industry specialization

Because firms from different industries can share similar technologies, banks' technology knowledge accumulated from past lending transcends industry boundaries. However, we cannot rule out completely an overlap of technology expertise with industry specialization.

[19]For example, this correlation may happen when a bank has a strong preference for borrowers with high-value (or low-value) technologies in certain technology classes. We control for lender fixed effects throughout, which to some extent mitigates the concern.

[20]In Table A3 in Appendix, we repeat all of the above regressions but replace the dependent variable all-in-drawn spreads with the natural logarithm of total loan costs from Berg et al. (2016). The use of total loan costs includes the various fees specific to each loan facility but reduces our sample size due to data availability. Nevertheless, we find again a robust negative association between borrower technology similarity and loan costs, statistically significant at the 1% level across all model specifications.

In the baseline results above, we partially address the concern by controlling for borrower segment similarity. A higher segment similarity indicates a larger overlap of the business lines of the borrower and the bank's existing borrowers, so that the bank may better leverage its industry specialization. We find that our results are robust to controlling for segment similarity.

To rule out the possibility that bank industry specialization drives our results, we repeat all of the above regressions but include the lender times industry times year fixed effects, which allow for time-varying bank industry specialization. Table 3 presents the results. We continue to find a negative and statistically significant relationship between borrower technology similarity and loan spreads across all model specifications. Moreover, the sizes of the estimated coefficients of technology similarity are even larger than in the baseline results. Therefore, although there is indeed some overlap of banks' technology knowledge and industry specialization, bank specialization does not drive our results, and that bank technology expertise contains information beyond industry specialization. Given that including lender times industry times year fixed effects reduces our sample size, we focus on our baseline model specification in the following analyses, but we note that all of our results are robust to controlling for bank industry specialization.

[**Insert Table 3 about here**]

In addition, we consider alternative industry classifications to further corroborate our results, including the Fama-French 48 industry classification and Hoberg and Phillips (2016) 10-K text-based 100 industries classification. Table A4 in the Appendix shows that, using alternative industry classifications, we continue to find a negative and statistically significant association between borrower technology similarity and loan spreads across all specifications with and without controlling for bank industry specialization via lender times industry times year fixed effects. As such, we are confident that our results are robust to industry definition and bank industry specialization does not drive our results.

B.2 Alternative construct of technology similarity

So far, our measure of bank technology knowledge of the borrower at loan origination is constructed by averaging the pairwise similarities of the borrower with each of the bank's prior borrowers. This method leads to a concern that we may accidentally introduce an attenuation bias. For example, a bank can have a strong technology knowledge of both biotechnology and semiconductor since it has existing borrowers that are respectively pure-play firms in biotechnology and semiconductor. Therefore, the bank should be well positioned in screening a new borrower that works in the intersection of biotechnology and semiconductor. However, the averaging of pairwise similarities could indicate that there is only limited overlap with existing borrowers, thus underestimating the bank's knowledge of the new borrower's technology.

To address this concern, we construct an alternative technology similarity measure. We first aggregate all of bank's prior borrowers as if they were one and build a portfolio of all patents of this "single" past borrower. We then compute the pairwise technology similarity between the new borrower and this technology portfolio aggregating all recent borrowers' patents. Mathematically, the cosine similarity of two vectors $\mathbf{A}$ and $\mathbf{B}$ is $\frac{\mathbf{A}\cdot\mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|}$. Our baseline method averaging pairwise similarities is $\frac{1}{N}\sum_i^N \frac{\mathbf{A}_i\cdot\mathbf{B}}{\|\mathbf{A}_i\|\|\mathbf{B}\|}$, and the alternative method is $\frac{(\sum \mathbf{A}_i)\cdot\mathbf{B}}{\|\sum \mathbf{A}_i\|\|\mathbf{B}\|}$, where $\mathbf{A}_i$ is the vector of patent classes of prior borrower i and $\mathbf{B}$ is the patent vector of the new borrower. This alternative measure contrasts averaging the pairwise technology similarities, which may lose valuable information about a bank's knowledge of new borrower's technology while the bank's technology knowledge learned from prior borrowers can be complementary and additive. As in the baseline, we use a 5-year window to construct the aggregate patent portfolio.

[Insert Table 4 about here]

Table 4 shows that our baseline results remain qualitatively unchanged. We note that the estimated coefficients of the alternative technology similarity measure are smaller in size than in the baseline. This, however, does not suggest that our baseline method is free of attenuation bias given that the alternative measure is a non-linear transformation. In Table A5 in the Appendix, we include lender times industry times year fixed effects and continue to find a negative and statistically significant relation between the alternative technology similarity measure and loan spreads across all model specifications.

On the other hand, both our baseline and the portfolio aggregation methods may still underestimate the bank's technology knowledge of the borrower, especially when the bank lends to many firms of different technologies in the past. In an extreme case, if the bank's past borrowers collectively own all technology classes, both methods will show a low level of technology similarity when the new borrower uses a small subset of technologies. To address this concern, we construct another alternative measure of borrower technology similarity that is the maximum pairwise similarity of the borrowing firm and the bank's past borrowers. We exclude the current borrowing firm from past borrowers because it creates a mechanical maximum pairwise similarity. Table A6 in the Appendix shows that, controlling for time-varying bank industry specialization, the relationship between the alternative measure based on maximum pairwise similarity and loan spreads remain negative and statistically significant across all model specifications.

The fact that we document a robust negative relation between borrower technology similarity and loan spreads in the presence of a potential attenuation bias and controlling for time-varying bank industry specialization suggests that banks technology knowledge accumulated from past lending indeed reduces loan costs.

B.3 Firm innovation, bank expertise, and relationship lending

Further, variations in technological similarity can come from both banks having no expertise and firms having no technology. Specifically, a technology similarity measure of zero can be result of either 1) the borrowing firm has patents, but these patents are dissimilar to the experience set of the bank (no bank technology expertise), or 2) the borrowing firm has no patents (no firm innovation). Given that the median technology similarity is zero in our sample, it is important to disentangle these two channels. We investigate the issue by removing borrowers without patents. As reported in Table 5, we continue to find a negative relationship (albeit weaker) between borrower technology similarity and loan spreads. This result suggests that our results are not driven by the second channel (no firm innovation).

[**Insert Table 5 about here**]

In addition, to address the concern that technology similarity may be higher when the bank has fewer recent borrowers and when the focal borrower is a major prior borrower, we perform two sub-sample analyses in Table 6. In columns (1) to (4), we remove the loans originated by the banks whose numbers of recent borrowers are in the bottom quartile. In columns (5) to (8), we remove the loans where the borrower is a major prior borrower of the bank defined by its loan amount in the top quartile. In both cases, we continue to find a negative association between borrower technology similarity and loan spreads, statistically significant at the 1% level.

[**Insert Table 6 about here**]

B.4 Placebo test

Lastly, we conduct a placebo test on whether interest rates are lower on borrowers who have similar technology to future borrowers. If our conjecture is correct, then there should be no relationship between a borrowing firm's technology similarity with the bank's future borrowers and the spreads of current loans. Specifically, at each loan's origination (time t), we compute the technology similarity of the borrowing firm and the bank's future borrowers from five years to ten years after loan origination ($t + 6$ to $t + 10$) so that there is no time overlap of when counting patent classes of the current and future borrowers (we use a five-year window to capture a firm's technology profile). As shown in Table A7 in the Appendix which replicates the baseline model using the placebo technology similarity, as expected, we find no significant relationship between the placebo measure and loan spreads across all specifications. This placebo test lends further support to our findings that banks accumulate technology knowledge from past lending activities, which helps reducing loan costs for future borrowers sharing similar technologies.

V Economic mechanisms

We now move on to investigate economic mechanisms underlying the negative effect of borrower technology similarity and loan costs. We start by showing that the technology similarity between a borrower and the bank's prior borrowers is informative about the borrower's creditworthiness, followed by a discussion of the empirical challenges for identification. To address the identification challenges, we then estimate a structural bank-borrower matching model similar to Schwert (2018) to show that such technology similarity is a major determinant of banks' lending decisions and endogenously a result of bank and borrower value maximization. Finally, we present difference-in-differences estimation results exploiting bank M&As to further strengthen our identification.

A The information content of technology similarity

In the screening process, why should a bank care about a borrower's technology similarity with the bank's prior borrowers? Extant studies have documented a vector of factors, beyond borrower fundamentals, from lending specialization, product market competition, supply chain relationship, innovation outputs to other soft information such as tax avoidance, stock price fragility and so on (e.g. Hasan et al., 2014; Campello & Gao, 2017; Chava et al., 2017; Hasan et al., 2021). The literature also highlights the importance of firms' technology profiles on future performance (e.g. Manso, 2011; Kogan et al., 2017). We argue that the technology similarity facilitates the bank to acquire opaque information from the borrower at reduced costs given its accumulated knowledge of prior borrowers' technology.

We empirically study the information content of a borrower's technology similarity with the bank's prior borrowers by studying the explanatory power of such technology similarity on the borrower's fundamentals and credit risks. Specifically, we regress the absolute difference in the borrowing firm's and the bank's prior borrowers' creditworthiness measures on their technology similarity, controlling for their segment similarity and a range of absolute differences in other firms' characteristics. Heteroskedasticity-robust standard errors are clustered at the borrower firm level.[21]

[Insert Table 7 about here]

Table 7 shows that a higher technology similarity is negatively associated with the absolute difference in borrowers' Altman Z-score, Merton (1974) default probability, profitability and cash holdings, all significant at the 1% level. These results imply that borrowers with similar technology profiles exhibit similar levels of creditworthiness and their capacities to service debt are relatively equal. Moreover, in Table A8, we find that a higher technology similarity predicts smaller absolute differences in borrowers' Altman Z-score, Merton (1974) default probability, profitability and cash holdings in the next five years. The empirical evidence is consistent to there being valuable information content embedded in the borrowers' overlapping technology capabilities and that this is relevant information for assessing the borrower's credit risk given the bank's knowledge of the prior borrowers' creditworthiness.

B Identification challenges

Given that technology similarity is informative about firm creditworthiness, a bank could potentially save on credit risk assessment costs when screening a borrower sharing similar technologies with the bank's prior borrowers. We find, in our baseline results, that banks pass on at least part of such savings to the borrower. However, an exact identification is

[21] Alternatively, our results are robust to clustering standard errors by bank or by borrower industry.

challenging for two reasons. First, an exogenous shock to the observed borrower technology similarity is unlikely. Because our measure of technology similarity is based on the borrowing firm's technology profile and that of the bank's prior borrowers, an ideal shock to the measure can only affect the borrowing firm's technology profile – extant borrowers' technology profiles are historical and cannot be affected, which then implies that the lending bank cannot be changed. Therefore, a candidate shock is one that exogenously alters the borrowing firm's technology profile and does not cause the firm to switch bank. We as econometricians, however, cannot know whether a new bank-borrower matching is a result of switching and whether a termination or suspension of a bank-borrower relationship is due to switching or other factors such as the firm's capital requirement. On the other hand, a changed technology profile is likely associated with significant changes in the borrower's business strategies and other fundamental aspects. Hence, a shock to the borrowing firm's technology profile more or less has impacts on other firm characteristics, thereby affecting bank-borrower matching and bank loan contracting. Simply put, it is challenging to employ traditional identification strategies involving difference-in-differences (DiD) estimations or instrumental variable (IV) regression analyses. For example, to the best of our knowledge, prior studies like Lee et al. (2019), McLemore et al. (2021), and Bereskin et al. (2022) encounter similar identification challenges.

To address the identification challenges, we use two methods to establish that banks benefit from lending to firms with technology profiles that are similar to their prior borrowers. With the benefits afforded, bank lenders willingly cut loan spreads to pass on the cost savings to borrowers. We first discuss and estimate a structural bank-borrower matching model to show that technology similarity plays a positive role in bank's value maximization. Further, given the aforementioned difficulty of finding an exogenous shock to the technology similarity itself, we instead exploit bank M&As as a reasonably exogenous shock to the stock of bank's technology knowledge using difference-in-differences (DiD) estimations.

C A structural bank-borrower matching model

In this section, we present and estimate a structural model of bank-borrower matching building on Fox (2017, 2018), Fox et al. (2018), and Schwert (2018) to show that the technology similarity between a borrower and bank's prior borrowers is a major determinant of the bank lending decision that results in a bank-borrower match (i.e., loan origination). Specifically, we are interested in how bank's technology knowledge of the borrower, as measured by the similarity measure at the time of loan origination, determines loan spread. However, we cannot observe any counterfactual bank-borrower matching assignments so that we do not have the loan spread a firm would pay if it borrowed from a different bank. The Fox (2018) model addresses this challenge by modelling transfer payments (e.g., the loan spread a firm pays to the bank) as unobservable in the equilibrium condition, and provides a way to estimate the model without data on transfer payments. The model thus enables us to identify the drivers of observed bank-borrower matching assignments in the absence of unobservable non-matching assignments.

In our context, applying the Fox (2018) model treats the observed bank-borrower matches (loans) as outcomes to be explained by a latent match value function. Estimating the function relies on the concept of pairwise stability in equilibrium, which states that neither the bank nor the borrower in an existing match would see an advantage in dissolving their current match in favor of matching with other firms or banks. Such pairwise stability condition leads to full stability under substitutable preferences (Schwert, 2018).

Formally, let there be a space of loans Ω, $\Psi \subseteq \Omega$ the set of borrowing activities for firm f and $\Phi \subseteq \Omega$ the set of lending activities for bank b. Given a value function $V_f(\Psi)$ for firm f, $V_b(\Phi)$ for bank b and total transfer payment (e.g., interests, fees, and other benefits) r_ι for loan $\iota \in \Omega$, the surplus for firm f borrowing loans Ψ is $V_f(\Psi) - \sum_{\iota\in\Psi} r_\iota$, and the surplus for bank b lending loans Φ is $V_b(\Phi) + \sum_{\iota\in\Phi} r_\iota$. Firm f and bank b search for Ψ and Φ, respectively, that maximize their own surpluses.

Consider two actual bank-borrower matches (b_1, f_1) and (b_2, f_2). From the bank's perspective, the pairwise stability condition states that for each bank-borrower match, the bank lending to the firm yields a higher value than to the other firm:

$$
\begin{aligned}
V_b(b_1, f_1) + r(b_1, f_1) &\geq V_b(b_1, f_2) + \underbrace{r(b_2, f_2) + [V_f(b_1, f_2) - V_f(b_2, f_2)]}_{\text{maximum } f_2 \text{ would pay } b_1 \text{ to switch from } b_2} \\
V_b(b_2, f_2) + r(b_2, f_2) &\geq V_b(b_2, f_1) + \underbrace{r(b_1, f_1) + [V_f(b_2, f_1) - V_f(b_1, f_1)]}_{\text{maximum } f_1 \text{ would pay } b_2 \text{ to switch from } b_1}
\end{aligned} \tag{4}
$$

Summing these pairwise stability conditions yields a condition without the transfer payments r, which is unobservable for counterfactual matches (b_1, f_2) and (b_2, f_1):[22]

$$
V(b_1, f_1) + V(b_2, f_2) \geq V(b_2, f_1) + V(b_1, f_2) \tag{5}
$$

where $V = V_b + V_f$, representing the total economic surplus for banks and borrowers (Schwert, 2018). Intuitively, such a condition implies that the actual matching assignments should lead to higher total surplus than counterfactual matches.[23] As a result, it shows that the value function is driven by the match characteristics rather than factors specific to banks or borrowers. Because the model considers all possible matching assignments, all bank and borrower characteristics enter the inequality on both sides and are hence canceled out.

To estimate the model, we follow Fox (2018) and Schwert (2018) and parameterize $V(b, f)$ as a linear function:

$$
V(b, f) = X'_{b\times f}\theta + \varepsilon_{b,f} \tag{6}
$$

where $X_{b\times f}$ represents the vector of bank-borrower match characteristics. The objective function for estimating the parameter vector θ developed by Fox (2018) is the sum of the indicators of all pairwise matching maximum score inequality (i.e., Equation 5), which takes

[22] The inequality condition in Equation 5 is at the core of Fox (2017) and Schwert (2018). Counterfactual bank-borrower matches (loans) have no observable transfer payments like loan spreads. If transfer payments remain in the inequality condition, the model cannot be estimated.

[23] Noticeably, the model uses a subset of all possible matching cases as it excludes counterfactuals such as a bank lending to both firms. However, Bajari et al. (2007) and Fox (2007) show that parameter estimates are consistent as long as more valuable matches are more likely to occur.

the following form with the linear parameterization of $V(b, f)$:

$$\mathcal{L}(\theta) = \sum_{t=1}^{T} \sum_{(b_m, f_n) \in G_t} \mathbb{1}[X'_{b_1 \times f_1}\theta + X'_{b_2 \times f_2}\theta \geq X'_{b_1 \times f_2}\theta + X'_{b_2 \times f_1}\theta] \tag{7}$$

where G_t denotes the set of all possible pairwise matching assignments, factual and counterfactual, in year t.[24] Following Schwert (2018), we restrict the samples to the loans with only one lead bank to avoid many-to-many matching complications.[25] Intuitively, maximizing the objective function aims to find the parameter θ that yields the higher occurrence of observed factual matching assignments. We solve for the maximum score estimator θ using the Particle Swarm Optimization (PSO).[26]

We note that the bank-borrower match characteristics $X_{b \times f}$ are observable even for counterfactual matching assignments. For example, assuming that bank A never lends to firm B, the counterfactual A-B match characteristics such as their geographical distance, the technology similarity (between firm B and bank A's prior borrowers) are still known. However, loan characteristics unobservable for counterfactual matches are necessarily excluded.[27] Following Schwert (2018), our match characteristic vector consists of a series of bank-borrower joint characteristics, including the borrower's bank-dependence, the bank-borrower geographical distance, prior lending relationship and the interactions of characteristics of the bank and

[24]Consistent with Schwert (2018), we consider each year as a separate market in which we construct counterfactual matches. Specifically, within a calendar year. More specifically, counterfactual matches are those bank-firm pairs that do not have a loan in the year.

[25]Schwert (2018) argue that many-to-many matching estimators are complicated to interpret in the case of bank-firm joint characteristics. He shows that all common panel multivariate regressions provide similar results for the sub-sample with only one lead arranger. Fox (2007) provide the theoretical foundation that maximum score estimators are consistent with the sub-sample analysis.

[26]The PSO method (Eberhart & Kennedy, 1995) uses a population (Swarm) of possible solutions (Particles), where possible solutions move around the search space guided by their own best-known positions as well as the whole population's optimal position (Bonyadi & Michalewicz, 2017). According to Fox (2018), the differential evolution (DE) method is an alternative option for solving the Equation 7. A comparison between PSO and DE could be found in Das et al. (2008). PSO does not use the gradient of the objective function and is less likely to end in a locally optimal point via searching a large space of candidate solutions, which is helpful in our setting with a large-size counterfactual matching sample. We appreciate the Mathematica code provided by Jeremy Fox.

[27]For example, we cannot observe the spread of a loan that never exists and would have to derive a pricing function should we attempt to include such loan characteristics into $X_{b \times f}$.

the borrower. More importantly, we include the borrower's technology similarity with the bank's prior borrowers, and additionally, the borrower product market rivalry effect using the Hoberg and Phillips (2016) Herfindahl-Hirschman Index.

[Insert Table 8 about here]

Table 8 presents the semi-parametric matching results and the point estimation of parameter vector θ. Given that the p-value is not obtainable in the parameter estimation of such an inequity condition, we compute confidence intervals following the Schwert (2018) bootstrapping method. The positive coefficients of technology similarity across all model specifications indicate that more value is generated by matching banks and borrowers with technology profiles that are similar to the banks' prior borrowers. Consistent with Schwert (2018), we find that well-capitalized banks are more likely to match with bank-dependent firms and that banks and firms located closer to each other or have prior lending relationships are also more likely to match. Similarly, we document a positive assortative matching by size, albeit statistically insignificant, possibly due to the reduced sample size as a result of requiring patent data. We further find that borrowers with more market power tend to match with larger or well-capitalized banks. Statistically, the fit of the model is excellent with over 98% of pairwise stability conditions satisfied by our estimated parameters, which is comparable to or better than the fit reported by Schwert (2018) and other earlier papers.[28]

Overall, our estimation of the bank-borrower matching model suggests an equilibrium market outcome where the total economic surplus for banks and borrower firms can be enhanced by matching banks with firms sharing similar technology profiles with banks' prior borrowers. This result provides strong evidence supporting our Hypothesis 1 that the borrower's technology similarity with bank's prior borrowers is informative and a significant factor in the bank's lending decision-making process.

[28]Schwert (2018) reports a fit of model where over 90% of pairwise stability conditions satisfied using the differential evolution algorithm.

D Difference-in-differences results

As discussed previously in section B, it is empirically challenging to find an exogenous shock to the technology similarity measure between a bank's new borrower and the bank's prior borrowers. However, if reduced information asymmetry and increased efficiency in screening and monitoring due to bank's accumulated technology knowledge are the mechanisms underlying the negative relationship between borrower technology similarity and loan spreads, we may alternatively exploit exogenous shocks to the stock of bank's technology knowledge using difference-in-differences (DiD) estimations, such as bank mergers and acquisitions (M&As). Bank M&As arguably increase acquirer banks' stock of accumulated technology knowledge, but do not affect their *extant* borrowers' creditworthiness and fundamentals. New borrowers of the acquirer bank (or the consolidated bank) after a M&A may confound our identification as their matching with the bank can be a result of endogenous selection. We therefore expect that after a bank M&A, extant borrowers of the acquirer bank will receive cheaper loans due to the exogenous positive shock on the bank's technology knowledge, compared to borrowers of other banks (without M&As).

Specifically, we start with a sample of 285 bank M&A deals from 1987 to 2019 from the updated DealScan lender link table by Schwert (2018). These M&As involve acquirer and/or target banks in the syndicated loan market and may provide acquirer banks better opportunities to improve efficiency via absorbing target banks' accumulated knowledge in assessing borrowers' technology profiles (Sapienza, 2002). We then filter out 12 bank-year M&A events as our shocks.[29] For each bank-year M&A event, we construct a cohort of treated banks and control banks with a five-year event window starting from two years

[29] We identify 31 unique acquirers (or the surviving entities after mergers) in the M&A deals by GVKEY in the updated DealScan lender link table by Schwert (2018). If a bank makes multiple M&A deals in a year, we collapse them into one event. Of the resulting 42 acquirer-year events, we keep 26 events by removing acquisitions by the same acquirer within any two consecutive years to avoid overlapping event windows. We further remove 3 acquisitions before the start of our sample period. Lastly, we drop the bank-year M&A events where the acquirer banks have no observations in Compustat Bank or loans in DealScan for the years either before or after the event year, including the M&A(s) made by Citibank, Bank of the West, NBD Bankcorp Inc., BB&T, BBVA, GE Capital, Wells Fargo & Co., and BankAmerica Business Credit. Table A9 in the Appendix lists the 12 bank-year M&A events and associated M&A deals.

before to two years after the event year. In each cohort, the treated bank is the bank that made one or more M&As in the event year, and control banks are those banks that have no M&A deals in the entire event window. If a bank has made a M&A deal, it is removed from all later cohorts as a control bank. Control banks in each cohort are the top-ten comparable banks selected using propensity score matching based on their bank size, non-deposit leverage, deposit ratio, and Tier 1 capital ratio. Table A10 in the Appendix verifies that our control banks and treated banks are comparable after the matching. Additionally, Figure A1 in the Appendix plots the average spreads of loans by the treated and control banks by years relative to the event year, which shows parallel changes in spreads before M&A events.

Using the sample of loans made by the treated banks to their extant borrowers, we then estimate the following DiD model:

$$\begin{aligned}\ln(\mathit{Loan\ Spread}_{m,i,l,c}) =&\beta_1 \mathit{Post}_{t,c} \times \mathit{Treated}_{m,i,l,c} + \beta_2 \mathit{Post}_{t,c} + \beta_3 \mathit{Treated}_{m,i,l,c} \\ &+ \beta_4 \Gamma_{i,l,c} + \text{Fixed Effects} + \varepsilon_{m,i,l,c}\end{aligned} \tag{8}$$

where $\mathit{Treated}_{m,i,l,c}$ is a dummy variable that equals to one, and zero otherwise, if loan l's lead bank m is the treated bank in cohort c. $\mathit{Post}_{t,c}$ is a dummy variable that equals one (zero) if year t in cohort c is after (before) the event year. $\Gamma_{i,l,t}$ represents loan and borrower characteristics as in the baseline. We include loan type and loan purpose fixed effects, borrower industry fixed effects and lender fixed effects. Heteoskedasticity-robust standard errors are double clustered at the bank and year levels.[30]

[Insert Table 9 about here]

Panel A of Table 9 shows that the coefficient estimates of the interaction term, $\mathit{Post} \times \mathit{Treated}$, are negative and statistically significant at the 5% level at least across all specifications, controlling for segment similarity, product market rivalry, patent stock, and patent value.

[30] Our results are robust to clustering standard errors at the borrower level.

Moreover, Panel B of Table 9 reports the results of a dynamic DiD model, where we replace the *Post* dummy variable in Equation 8 with the indicator variable $D_{c,\tau}$ ($\tau = -1, 0, 1, 2$) that equals one if the loan is issued τ years after the event year in cohort c and zero otherwise. We confirm that the treatment effect occurs only in the year(s) after the event year, with a visualization in Figure A2 in the Appendix. These results are consistent with our expectation that, as acquirer banks obtain the accumulated technology knowledge from target banks after a M&A, the increased stock of technology knowledge allows the banks to improve their screening and monitoring on borrowers' technology profiles, leading to reduced loan spreads.[31] Our results suggest that the documented negative relation between borrower technology similarity and loan costs is likely causal.

VI Further results

Lastly, we explore the heterogeneous effects of borrower technology similarity on bank loan pricing from both bank and borrower perspectives. Our Hypotheses 2 and 3 conjecture that borrowers sharing similar technology profiles with the banks' prior borrowers receive lower loan spreads, especially for smaller, less-capitalized or low-liquidity banks and less risky borrowers. Specifically, we include the relevant bank or borrower characteristics and their interaction with technology in the baseline model. We control for the industry segment similarity between the borrower and the bank's prior borrowers, the intensity of borrower product market competition, as well as the borrower's technology stock and value.

[Insert Table 10 about here]

Table 10 shows the heterogeneous effects of borrower technology similarity on bank loan spreads from the bank's perspective. Column (1) shows that borrower technology similarity remains negatively and significantly associated with loan spreads after the inclusion of bank

[31] Our results are also consistent with Erel (2011) that bank mergers decrease loan spreads when gains from cost savings outweigh the increase of bank market power.

size and its interaction with borrower technology similarity. The positive and significant coefficient of the interaction term confirms that smaller banks cut loan spreads more than larger banks given a higher borrower technology similarity. In column (2), we include the bank's Tier 1 capital ratio and its interaction with borrower technology similarity. We find that the negative and significant association between borrower technology similarity and loan spreads remains qualitatively unchanged, and is stronger for banks with a lower Tier 1 capital ratio. In column (3), we include bank (il)liquidity (following Acharya & Mora, 2015) and the loan-to-deposit shortfall, as well as their interactions with borrower technology similarity. We find that the interaction between bank loan-to-deposit shortfall and borrower technology similarity is negative and statistically significant, which implies that less liquid banks reduce loan spreads for borrowers with similar technology profiles compared to prior borrowers.

[Insert Table 11 about here]

Table 11 reports the heterogeneous effects of technology similarity on bank loan spreads from the borrower's perspective. In column (1) we interact the borrower creditworthiness measured by the Altman Z-score and borrower technology similarity. We find that the negative and significant coefficient of the interaction terms drives out the statistical significance of borrower technology similarity, which continues to have a negative estimate. This result suggests that the documented negative effect of borrower technology similarity on loan costs mainly comes from safer borrowers.[32] In column (2), we investigate borrower leverage and find that the coefficient of its interaction with borrower technology similarity is positive and significant. This result shows that less-leveraged borrowers are granted lower loan spreads than more-leveraged ones when they share similar technology profiles with the bank's extant borrowers. In column (3), we interact borrower profitability and our technology similarity measure and find a negative and significant coefficient estimate of the interaction term, which drives out the statistical significance of technology similarity. This implies that banks

[32] We find similar results using alternative borrower creditworthiness measures such as the borrower default probability and whether the borrower has a credit rating.

are more willing to reduce loan spreads for profitable borrowers when they have a higher technology similarity with banks' prior borrowers.

To test our Hypothesis 4 that banks charge lower loan spreads for borrowers that share similar technologies with the banks' prior borrowers especially when their technological obsolescence is low, we use borrowers' technological obsolescence as in Ma (2021). Following Ma (2021), the technology base for a firm i in year t is predetermined as all other firms' patents cited by firm i up to year $t - \omega$. The technological obsolescence of firm i in year t is then calculated as the negative of the log difference in the external citations of the firm's technology base in year t and in year $t - \omega$. Our estimates are comparable to that in Ma (2021).[33] But to minimise the impact of measurement error, we calculate two proxies. The first is a dummy variable that takes the value of 1 if a borrower's technological obsolescence is below the annual median, and 0 otherwise. The second is the annual decile rank of borrowers' technological obsolescence. We then interact each of the two proxies with borrower technology similarity. Table 12 presents the results.

[**Insert Table 12 about here**]

Columns (1) to (4) of Table 12 show that the interaction term of borrower technology similarity and low technological obsolescence dummy is negative and statistically significant, whether or not we control for other known technology measures such as patent stock and patent value. Moreover, we find that the coefficient estimates of technology similarity itself are no longer significant, which suggests that banks' technological expertise may only reduce loan spreads when the borrowers' technologies are not obsolete. In columns (5) to (8), we confirm that the more obsolete a borrower's technologies are, the lower the effect of technology similarity on loan spreads. These results support our Hypothesis 4.

In summary, we show that it is the smaller, less-capitalized, or less-liquid banks that tend

[33] In Ma (2021), a firm's technology base includes a mean (median) of 2,001 (219) patents. In our calculation, the mean (median) technology base is 2,223 (173). The technological obsolescence estimates have a mean of 12.9% ($\omega = 3$) and 19.39% ($\omega = 5$) in Ma (2021), and a mean of 11.3% ($\omega = 3$) and 14.9% ($\omega = 5$) in our estimates. The discrepancies may be due to different filters applied on the sample.

to charge lower loan spreads for borrowers sharing a higher technology similarity with their prior borrowers. The reward for borrower technology similarity on loan spreads is stronger for creditworthy, profitable or less-leveraged firms, and is mostly clustered in borrowers with low technological obsolescence.

VII Conclusion

In this study, we empirically examine the impact of borrower technology similarity on the cost of bank loans. We show that banks charge lower loan spreads for borrowers that share a similar technology profile with the banks' prior borrowers, likely due to the cost savings from the reduced due diligence needed in assessing the borrowers' technologies and implications for their credit risk profiles. Such effect is robust to alternative constructs of borrower technology similarity, controlling for the industry segment similarity between the borrower and prior borrowers which affects the bank loan portfolio's industry concentration, and controlling for the intensity of product market competition faced by the borrower. Furthermore, the borrower's technology profile itself as measured by patent value and stock does not absorb the effect of its similarity with the bank's prior borrowers on loan costs, even after controlling for relationship lending. We further rule out the possibility that bank industry specialization drives our results.

Despite the identification challenges, we show that borrower technology similarity is informative about firm creditworthiness and debt service capability. We present and estimate a structural bank-borrower matching model to show that borrower technology similarity is an important determinant in bank lending decisions, which plays a positive role in the simultaneous value maximization of both banks and borrowers. The total economic surplus for banks and borrowers can be enhanced by matching banks to borrowers with a similar technology profile to the banks' prior borrowers. We then use difference-in-differences estimations to show that after exogenous positive shocks to banks' accumulated technology knowledge, banks reduce loan spreads to their borrowers. Specifically, we find that smaller, less-capitalized, or less-liquid banks give larger discounts in loan pricing for borrowers with a higher technology similarity to the banks' prior borrowers. Furthermore, banks reward the safer, more profitable and less indebted borrowers with less technological obsolescence. We find that these borrowers are systematically granted cheaper loans by bank lenders in the syndicated loan market.

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Figure 1: **Pairwise Technology Similarity**

Figure 1 illustrates the pairwise technology similarity calculation for a borrower firm i, at loan origination time t, for the two prior borrowers j and k of the bank in the five years leading to t. The degree of technology similarity is computed based on the patent portfolios of borrower j and k as at their respective borrowing time, instead of time t, and the portfolio of firm i as at time t. This specification builds on the assumption that the lending bank learns about a borrower's patent portfolio at loan origination.

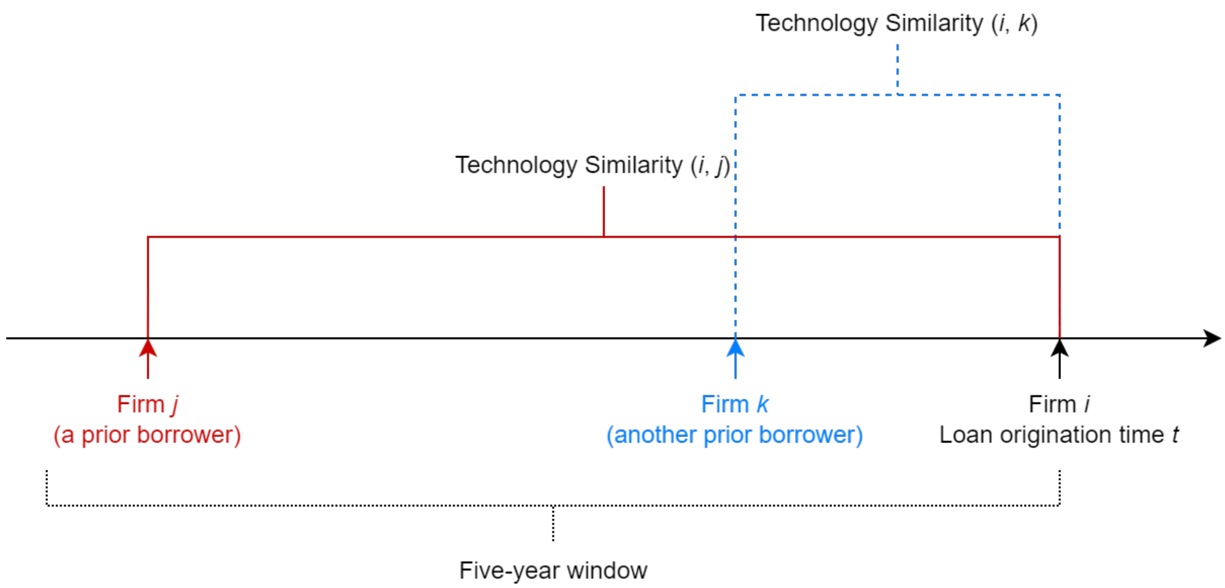

Table 1: **Summary Statistics**

Table 1 presents the summary statistics of our loan sample sourced from DealSCan, which consists of 36,166 loans to U.S. borrowers (excluding utility and financial firms) from January 1990 to December 2020. Definitions of the variables are provided in Table A1 in the Appendix. All continuous variables are winsorized by year at the 1st and 99th percentiles.

	Observations	Mean	Standard Deviation	10^{th} Percentile	Median	90^{th} Percentile
Bank-borrower characteristics						
Technology Similarity	36,166	0.039	0.060	0.000	0.000	0.132
Segment Similarity	36,166	0.063	0.056	0.008	0.052	0.125
Prior Relationship	36,166	0.355	0.379	0.000	0.239	1.000
Borrower In Bank Top Industries	36,166	0.190	0.392	0	0	1
Lending Relationship Time	36,166	1.940	2.838	0.000	1.000	6.000
Loan characteristics						
Loan Spread (bps)	36,166	205.310	141.397	50.000	175.000	375.000
ln(Loan Spread)	36,166	5.066	0.782	3.912	5.165	5.927
Loan Size ($ millions)	36,166	425.155	739.765	14.201	166.000	1045.000
Loan Maturity (months)	36,166	48.193	22.538	12.000	60.000	72.000
Loan Secured	36,166	0.533	0.499	0	1	1
Borrower characteristics						
Borrower Product Market HHI	36,166	0.283	0.264	0.049	0.184	0.689
Borrower Product Market Similarity	36,166	3.133	3.991	1.019	1.578	7.050
Borrower Product Market Fluidity	36,166	6.624	3.426	2.888	5.961	11.254
Borrower Patent Stock	36,166	0.566	4.398	0.000	0.000	0.492
Borrower Citation Stock	36,166	1.865	2.800	0.000	0.000	6.372
Borrower Patent Value	36,166	5.607	26.663	0.000	0.000	10.959
Borrower Size	36,166	7.074	1.942	4.498	7.101	9.642
Borrower Total Assets ($ billions)	36,166	6.566	19.569	0.088	1.213	15.399
Borrower Leverage	36,166	0.314	0.212	0.037	0.297	0.584
Borrower Z-score	36,166	0.016	0.014	0.001	0.015	0.032
Borrower Profitability	36,166	0.128	0.089	0.048	0.125	0.227
Borrower Market-to-Book	36,166	0.028	0.053	0.007	0.021	0.059
Borrower Cash	36,166	0.074	0.090	0.005	0.040	0.189
Borrower Has Credit Rating	36,166	0.519	0.500	0	1	1
Borrower Default Probability	28,120	0.027	0.083	0.000	0.000	0.066
Bank characteristics						
Bank Size	30,485	13.159	1.419	11.205	13.401	14.674
Bank Capital	28,764	0.113	0.052	0.050	0.112	0.172
Bank Tier 1 Capital Ratio (%)	28,764	9.932	2.484	7.350	8.700	13.460
Bank Loan-to-Deposit Shortfall	30,518	-0.115	0.092	-0.209	-0.116	-0.005

Table 2: **Borrower Technology Similarity and Loan Spread**

Table 2 reports the results of regressing the natural logarithm of all-in-drawn loan spreads on borrower technology similarity. Specifically, column (1) reports the baseline result. Column (2) controls for the borrower's segment similarity with bank's prior borrowers. Columns (3) through (5) control for the competition faced by the borrower using three of Hoberg and Phillips (2016) product market competition measures, respectively. Columns (6) to (8) additionally control for the borrower's patent value and patent stock, as well as the segment similarity. In all specifications, we control for bank-borrower prior lending relationship, borrower characteristics, loan characteristics, and fixed effects for loan type, loan purpose, borrower industry – year, and lender. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are heteroskedasticity-robust standard errors clustered at the borrower level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Technology Similarity	-0.380***	-0.412***	-0.362***	-0.373***	-0.350***	-0.309***	-0.318***	-0.291***
	(0.093)	(0.094)	(0.092)	(0.093)	(0.092)	(0.094)	(0.095)	(0.094)
Segment Similarity		0.224**				0.218**	0.219**	0.194**
		(0.094)				(0.094)	(0.094)	(0.093)
Borrower Product Market HHI			-0.113***			-0.112***		
			(0.020)			(0.020)		
Borrower Product Market Similarity				0.004***			0.004***	
				(0.001)			(0.001)	
Borrower Product Market Fluidity					0.014***			0.014***
					(0.002)			(0.002)
Borrower Patent Value						-0.001***	-0.001***	-0.001***
						(0.000)	(0.000)	(0.000)
Borrower Patent Stock						-0.001	-0.001	-0.001
						(0.001)	(0.001)	(0.001)
Prior Relationship	-0.019*	-0.022**	-0.020*	-0.020*	-0.020*	-0.024**	-0.025**	-0.024**
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Borrower Size	-0.085***	-0.085***	-0.088***	-0.086***	-0.089***	-0.083***	-0.081***	-0.084***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Borrower Leverage	0.566***	0.566***	0.574***	0.569***	0.571***	0.564***	0.559***	0.560***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Borrower Z-score	-2.007***	-1.984***	-1.819***	-1.838***	-1.369***	-1.888***	-1.896***	-1.436***
	(0.442)	(0.443)	(0.441)	(0.445)	(0.447)	(0.439)	(0.442)	(0.444)
Borrower Profitability	-1.136***	-1.135***	-1.139***	-1.138***	-1.144***	-1.113***	-1.111***	-1.116***
	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)	(0.062)	(0.062)	(0.062)
Borrower Market-to-Book	-0.323***	-0.323***	-0.315***	-0.331***	-0.338***	-0.275***	-0.291***	-0.297***
	(0.073)	(0.073)	(0.073)	(0.073)	(0.074)	(0.070)	(0.071)	(0.072)
Borrower Cash	0.090*	0.091*	0.061	0.075	0.037	0.065	0.078	0.040
	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.048)
Borrower Has Credit Rating	0.039***	0.039***	0.039***	0.039***	0.040***	0.035***	0.035***	0.036***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.011)	(0.012)	(0.011)
ln(Loan Size)	-0.097***	-0.096***	-0.097***	-0.097***	-0.097***	-0.097***	-0.097***	-0.097***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
ln(Loan Maturity)	0.016**	0.016**	0.017**	0.017**	0.017**	0.014**	0.014*	0.014*
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Loan Secured	0.385***	0.385***	0.384***	0.385***	0.380***	0.383***	0.384***	0.380***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Loan Type and Purpose Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Industry × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,166	36,166	36,166	36,166	36,166	36,166	36,166	36,166
Adjusted R^2	0.653	0.653	0.654	0.653	0.655	0.656	0.655	0.657

Table 3: **Borrower Technology Similarity and Loan Spread Controlling for Time-varying Bank Industry Specialization**

Table 3 reports the results of estimating all the model specifications as in Table 2, additionally controlling for time-varying bank industry specialization via lender times industry times year fixed effects. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are heteroskedasticity-robust standard errors clustered at the borrower level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Technology Similarity	-0.444***	-0.483***	-0.426***	-0.438***	-0.408***	-0.371***	-0.380***	-0.341***
	(0.125)	(0.128)	(0.122)	(0.124)	(0.123)	(0.127)	(0.130)	(0.128)
Segment Similarity		0.296				0.335*	0.335*	0.272
		(0.199)				(0.200)	(0.200)	(0.197)
Borrower Product Market HHI			-0.150***			-0.151***		
			(0.025)			(0.025)		
Borrower Product Market Similarity				0.004***			0.005***	
				(0.002)			(0.002)	
Borrower Product Market Fluidity					0.016***			0.016***
					(0.002)			(0.002)
Borrower Patent Stock						-0.001	-0.001	-0.001
						(0.001)	(0.001)	(0.001)
Borrower Patent Value						-0.001***	-0.001***	-0.001***
						(0.000)	(0.000)	(0.000)
Prior Relationship	-0.046***	-0.046***	-0.047***	-0.047***	-0.046***	-0.049***	-0.049***	-0.048***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Borrower Size	-0.097***	-0.097***	-0.101***	-0.098***	-0.102***	-0.095***	-0.091***	-0.095***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Borrower Leverage	0.665***	0.665***	0.673***	0.667***	0.665***	0.660***	0.654***	0.651***
	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
Borrower Z-score	-2.859***	-2.850***	-2.605***	-2.661***	-2.164***	-2.723***	-2.761***	-2.276***
	(0.537)	(0.538)	(0.536)	(0.541)	(0.544)	(0.534)	(0.539)	(0.542)
Borrower Profitability	-1.191***	-1.191***	-1.193***	-1.193***	-1.199***	-1.161***	-1.161***	-1.166***
	(0.082)	(0.082)	(0.082)	(0.082)	(0.082)	(0.081)	(0.082)	(0.082)
Borrower Market-to-Book	-0.381***	-0.383***	-0.376***	-0.391***	-0.391***	-0.341***	-0.357***	-0.355***
	(0.087)	(0.087)	(0.086)	(0.088)	(0.089)	(0.083)	(0.085)	(0.086)
Borrower Cash	0.160**	0.160**	0.120*	0.143**	0.100	0.123**	0.145**	0.102
	(0.064)	(0.064)	(0.063)	(0.064)	(0.063)	(0.063)	(0.063)	(0.063)
Borrower Has Credit Rating	0.038***	0.038***	0.037***	0.038***	0.040***	0.033**	0.034**	0.035***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
ln(Loan Size)	-0.081***	-0.081***	-0.081***	-0.081***	-0.082***	-0.082***	-0.082***	-0.082***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
ln(Loan Maturity)	0.034***	0.034***	0.034***	0.034***	0.034***	0.032***	0.033***	0.032***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Loan Secured	0.352***	0.352***	0.349***	0.351***	0.347***	0.350***	0.352***	0.347***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Loan Type and Purpose Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender × Borrower Industry × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31,578	31,578	31,578	31,578	31,578	31,578	31,578	31,578
Adjusted R^2	0.729	0.729	0.730	0.729	0.731	0.731	0.731	0.732

Table 4: **Alternative Borrower Technology Similarity Measure**

Table 4 reports the results of regressing the natural logarithm of all-in-drawn loan spreads on the alternative technology similarity measure calculated as the pairwise similarity between the borrower and the aggregate patent portfolio of the bank's recent borrowers within the 5-year window. Specifically, column (1) reports the baseline result. Column (2) controls for the borrower's segment similarity with bank's prior borrowers. Columns (3) through (5) control for the competition faced by the borrower using three of Hoberg and Phillips (2016) product market competition measures, respectively. Columns (6) to (8) additionally control for the borrower's patent value and patent stock, as well as the segment similarity. In all specifications, we control for bank-borrower prior lending relationship, borrower characteristics, loan characteristics, and fixed effects for loan type, loan purpose, borrower industry – year, and lender. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are heteroskedasticity-robust standard errors clustered at the borrower level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Technology Similarity (Portfolio)	-0.135***	-0.143***	-0.129***	-0.132***	-0.124***	-0.102***	-0.104***	-0.095***
	(0.034)	(0.034)	(0.033)	(0.034)	(0.033)	(0.034)	(0.034)	(0.034)
Segment Similarity (Portfolio)		0.109***				0.094**	0.094**	0.078**
		(0.041)				(0.040)	(0.040)	(0.040)
Borrower Product Market HHI			-0.113***			-0.110***		
			(0.020)			(0.020)		
Borrower Product Market Similarity				0.004***			0.004***	
				(0.001)			(0.001)	
Borrower Product Market Fluidity					0.014***			0.014***
					(0.002)			(0.002)
Borrower Patent Stock						-0.001	-0.001	-0.001
						(0.001)	(0.001)	(0.001)
Borrower Patent Value						-0.001***	-0.001***	-0.001***
						(0.000)	(0.000)	(0.000)
Prior Relationship	-0.022**	-0.027**	-0.022**	-0.022**	-0.022**	-0.029***	-0.029***	-0.028***
	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Borrower Size	-0.085***	-0.086***	-0.088***	-0.086***	-0.089***	-0.084***	-0.081***	-0.084***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Borrower Leverage	0.566***	0.567***	0.574***	0.569***	0.571***	0.565***	0.560***	0.561***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Borrower Z-score	-2.005***	-1.940***	-1.817***	-1.839***	-1.369***	-1.855***	-1.876***	-1.415***
	(0.442)	(0.442)	(0.440)	(0.445)	(0.446)	(0.438)	(0.442)	(0.444)
Borrower Profitability	-1.136***	-1.138***	-1.139***	-1.137***	-1.143***	-1.115***	-1.113***	-1.118***
	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)	(0.062)	(0.062)	(0.062)
Borrower Market-to-Book	-0.324***	-0.323***	-0.315***	-0.332***	-0.339***	-0.275***	-0.291***	-0.298***
	(0.073)	(0.073)	(0.073)	(0.073)	(0.074)	(0.070)	(0.071)	(0.072)
Borrower Cash	0.095*	0.091*	0.065	0.080	0.041	0.065	0.079	0.041
	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.048)	(0.049)	(0.048)
Borrower Has Credit Rating	0.039***	0.039***	0.039***	0.039***	0.040***	0.035***	0.035***	0.036***
	(0.012)	(0.012)	(0.011)	(0.012)	(0.011)	(0.011)	(0.012)	(0.011)
ln(Loan Size)	-0.096***	-0.096***	-0.097***	-0.097***	-0.097***	-0.097***	-0.097***	-0.097***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
ln(Loan Maturity)	0.016**	0.016**	0.016**	0.016**	0.016**	0.014*	0.014*	0.014*
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Loan Secured	0.385***	0.384***	0.383***	0.384***	0.380***	0.382***	0.383***	0.379***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Loan Type and Purpose Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Industry × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,166	36,166	36,166	36,166	36,166	36,166	36,166	36,166
Adjusted R^2	0.653	0.653	0.654	0.653	0.655	0.656	0.655	0.657

Table 5: **Sub-sample Analysis: Removing Firms without Patents**

Table 5 reports the sub-sample analysis results where we restrict to the loans to borrowers with patents. Specifically, column (1) reports the baseline result. Column (2) controls for the borrower's segment similarity with bank's prior borrowers. Columns (3) through (5) control for the competition faced by the borrower using three of Hoberg and Phillips (2016) product market competition measures, respectively. Columns (6) to (8) additionally control for the borrower's patent value and patent stock, as well as the segment similarity. In all specifications, we control for bank-borrower prior lending relationship, borrower characteristics, loan characteristics, and fixed effects for loan type, loan purpose, borrower industry – year, and lender. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are heteroskedasticity-robust standard errors clustered at the borrower level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Technology Similarity	-0.234**	-0.269**	-0.215**	-0.228**	-0.202*	-0.201*	-0.210*	-0.180*
	(0.107)	(0.109)	(0.106)	(0.107)	(0.106)	(0.108)	(0.109)	(0.109)
Segment Similarity		0.224*				0.224*	0.214*	0.193
		(0.125)				(0.125)	(0.124)	(0.123)
Borrower Product Market HHI			-0.134***			-0.135***		
			(0.025)			(0.025)		
Borrower Product Market Similarity				0.006***			0.006***	
				(0.002)			(0.002)	
Borrower Product Market Fluidity					0.014***			0.015***
					(0.003)			(0.002)
Borrower Patent Stock						-0.000	-0.000	-0.000
						(0.001)	(0.001)	(0.001)
Borrower Patent Value						-0.001***	-0.001***	-0.001***
						(0.000)	(0.000)	(0.000)
Prior Relationship	-0.027*	-0.029*	-0.026*	-0.026*	-0.025*	-0.030**	-0.030**	-0.028*
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Borrower Size	-0.082***	-0.082***	-0.087***	-0.083***	-0.086***	-0.081***	-0.077***	-0.080***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
Borrower Leverage	0.645***	0.644***	0.655***	0.652***	0.655***	0.639***	0.636***	0.638***
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
Borrower Z-score	-1.919***	-1.911***	-1.624***	-1.622***	-1.120*	-1.761***	-1.732***	-1.239**
	(0.593)	(0.594)	(0.590)	(0.600)	(0.609)	(0.587)	(0.595)	(0.605)
Borrower Profitability	-1.150***	-1.148***	-1.152***	-1.155***	-1.169***	-1.117***	-1.120***	-1.134***
	(0.092)	(0.093)	(0.092)	(0.093)	(0.092)	(0.090)	(0.092)	(0.091)
Borrower Market-to-Book	-0.520***	-0.519***	-0.514***	-0.533***	-0.541***	-0.450***	-0.468***	-0.475***
	(0.110)	(0.110)	(0.109)	(0.110)	(0.111)	(0.104)	(0.106)	(0.107)
Borrower Cash	0.083	0.083	0.033	0.056	0.015	0.038	0.058	0.019
	(0.068)	(0.068)	(0.067)	(0.068)	(0.067)	(0.066)	(0.068)	(0.067)
Borrower Has Credit Rating	0.022	0.022	0.023	0.023	0.023	0.018	0.018	0.019
	(0.017)	(0.017)	(0.016)	(0.017)	(0.017)	(0.016)	(0.017)	(0.016)
ln(Loan Size)	-0.104***	-0.104***	-0.105***	-0.104***	-0.104***	-0.105***	-0.104***	-0.104***
	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)
ln(Loan Maturity)	0.033***	0.033***	0.033***	0.033***	0.033***	0.030***	0.030***	0.030***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Loan Secured	0.421***	0.421***	0.417***	0.420***	0.415***	0.417***	0.419***	0.415***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Loan Type and Purpose Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Industry × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,881	20,881	20,881	20,881	20,881	20,881	20,881	20,881
Adjusted R^2	0.682	0.682	0.683	0.683	0.684	0.685	0.684	0.685

Table 6: **Sub-sample Analysis: Removing Banks with Few Borrowers and Loans to Major Customers**

Table 6 reports sub-sample analysis results. Specifically, in columns (1) to (4), we remove the loans originated by the banks whose numbers of recent borrowers are in the bottom annual quartile. In columns (5) to (8), we remove the loans where the borrower is a major prior borrower of the bank defined by its loan amount in the top annual quartile. In all specifications, we control for borrower characteristics, loan characteristics, and fixed effects for loan type, loan purpose, borrower industry – year, and lender. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are heteroskedasticity-robust standard errors clustered at the borrower level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Remove banks with few recent borrowers				Remove loans to major prior borrowers			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Technology Similarity	-0.348***	-0.317***	-0.343***	-0.309***	-0.386***	-0.334***	-0.386***	-0.331***
	(0.098)	(0.096)	(0.098)	(0.096)	(0.106)	(0.103)	(0.106)	(0.103)
Segment Similarity	0.132		0.158		0.249**		0.249**	
	(0.106)		(0.106)		(0.117)		(0.117)	
Borrower Product Market HHI		-0.104***		-0.104***		-0.096***		-0.096***
		(0.021)		(0.021)		(0.022)		(0.022)
Prior Relationship			-0.037***	-0.036***	-0.036***		-0.036***	-0.035***
			(0.011)	(0.011)	(0.013)		(0.013)	(0.013)
Borrower Size	-0.078***	-0.081***	-0.079***	-0.082***	-0.073***	-0.075***	-0.073***	-0.076***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
Borrower Leverage	0.552***	0.560***	0.554***	0.561***	0.546***	0.552***	0.546***	0.553***
	(0.028)	(0.028)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Borrower Z-score	-2.285***	-2.121***	-2.239***	-2.079***	-2.434***	-2.324***	-2.434***	-2.289***
	(0.453)	(0.451)	(0.453)	(0.451)	(0.466)	(0.466)	(0.466)	(0.465)
Borrower Profitability	-1.133***	-1.137***	-1.129***	-1.132***	-1.007***	-1.013***	-1.007***	-1.009***
	(0.067)	(0.066)	(0.067)	(0.066)	(0.068)	(0.068)	(0.068)	(0.068)
Borrower Market-to-Book	-0.318***	-0.311***	-0.320***	-0.313***	-0.336***	-0.327***	-0.336***	-0.329***
	(0.073)	(0.072)	(0.073)	(0.072)	(0.078)	(0.078)	(0.078)	(0.078)
Borrower Cash	0.088*	0.061	0.078	0.051	0.067	0.047	0.067	0.040
	(0.051)	(0.051)	(0.051)	(0.051)	(0.052)	(0.052)	(0.052)	(0.052)
Borrower Has Credit Rating	0.036***	0.036***	0.036***	0.036***	0.038***	0.038***	0.038***	0.038***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
ln(Loan Size)	-0.097***	-0.098***	-0.096***	-0.097***	-0.098***	-0.099***	-0.098***	-0.098***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
ln(Loan Maturity)	0.036***	0.036***	0.035***	0.036***	0.032***	0.033***	0.032***	0.032***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Loan Secured	0.381***	0.379***	0.380***	0.378***	0.367***	0.366***	0.367***	0.366***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)
Loan Type and Purpose Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Industry × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	32,555	32,555	32,555	32,555	24,316	24,316	24,316	24,316
Adjusted R^2	0.658	0.658	0.658	0.659	0.634	0.634	0.634	0.634

Table 7: **Information Content of Technology Similarity**

Table 7 examines the explanatory power of a borrower's technology similarity with its bank's prior borrowers for the difference in their creditworthiness. Specifically, we regress the absolute difference of borrower's and bank's prior borrowers' average creditworthiness measures on their technology similarity, controlling for their segment similarity and absolute differences across an array of firm characteristics. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are heteroskedasticity-robust standard errors clustered at the borrower level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable (Absolute Difference):	Z-score	Default Probability	Profitability	Cash Holding
	(1)	(2)	(3)	(4)
Technology Similarity	-0.005***	-0.037***	-0.056***	-0.038***
	(0.002)	(0.013)	(0.010)	(0.011)
Segment Similarity	-0.004	0.008	-0.040***	-0.037***
	(0.002)	(0.015)	(0.013)	(0.012)
Absolute difference in size	0.001***	-0.002**	0.004***	0.002***
	(0.000)	(0.001)	(0.001)	(0.001)
Absolute difference in leverage	0.017***	0.122***	0.062***	0.048***
	(0.001)	(0.009)	(0.006)	(0.005)
Absolute difference in market-to-book ratio	0.009***	-0.022	0.204***	0.050***
	(0.002)	(0.015)	(0.020)	(0.015)
Absolute difference in sales growth	0.000***	-0.000*	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Absolute difference in tangibility	0.003***	0.009	-0.010**	0.012**
	(0.001)	(0.007)	(0.005)	(0.005)
Absolute difference in patent stock	-0.037	0.293	-0.110	-0.055
	(0.025)	(0.219)	(0.093)	(0.194)
Absolute difference in patent value	0.000**	-0.000**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Industry and Year Fixed Effects	Yes	Yes	Yes	Yes
Lender Fixed Effects	Yes	Yes	Yes	Yes
Observations	36,166	28,074	36,166	36,166
Adjusted R^2	0.238	0.258	0.209	0.130

Table 8: **Structural Bank-Borrower Matching Model Estimation**

Table 8 shows the result of the semi-parametric bank-borrower matching model following the Fox (2018) framework. We follow Schwert (2018) to create a series of bank-firm joint characteristics. The key variable of interest is borrowers' technology similarity. Technology similarity measurement is specific at the lender-borrower level each year (or each independent market in our semi-parametric matching setting). Following Abrevaya and Huang (2005), we define the significance of the point estimate using the 95% confidence interval which is generated by drawing 1,000 sub-samples with replacement. We present 95% confidence interval in parentheses below the corresponding coefficient with statistical significance denoted as follows: ** (if the point estimate is within the 95 % confidence interval).

	Point Estimation of the Parametric Vector				
	(1)	(2)	(3)	(4)	(5)
Technology Similarity	7.265**	7.773**	9.013**	9.753**	8.841**
	[4.009, 15.192]	[4.562, 17.449]	[5.207, 18.449]	[5.743, 16.598]	[5.308 ,17.491]
Borrower Bank-Dependent × Bank Capital	9.839**	6.305**	9.704**	12.034**	10.598**
	[7.547, 16.332]	[5.887, 9.437]	[6.572, 12.846]	[2.218, 17,754]	[6.119, 10.880]
ln(Geographic Distance)	-2.507**	-2.038**	-1.094**	-3.253**	
	[-5.647, -0.933]	[-5.043, -0.386]	[-2.345, -0.994]	[-4.510, -1.357]	
Borrower Size × Bank Size	0.528	0.012	0.185		0.124
	[-0.536, 1.405]	[-2.095, 0.009]	[-1.386, 0.452]		[-0.604, 0.357]
Borrower Product Market HHI × Bank Size	2.942**	0.019		0.271	1.066
	[0.126, 8.883]	[-4.720, 5.474]		[-3.272, 3.815]	[-5.330, 2.597]
Borrower In Bank Top Industries	9.957**		6.947**	2.818**	5.411**
	[6.938, 12.977]		[5.545, 8.403]	[1.090, 3.369]	[3.304, 7.518]
Prior Relationship	5.570**	5.868**	8.401**	2.975**	9.496**
	[3.536, 7.493]	[3.618, 8.472]	[5.641, 13.161]	[1.299, 3.876]	[5.987, 14.012]
Number of Inequalities	573,835	573,835	573,835	573,835	573,835
Satisfied Inequalities	0.99	0.98	0.98	0.96	0.98

Table 9: **Difference-in-Differences Estimation: Bank M&A**

Table 9 shows the results of the difference-in-differences (DiD) estimation using bank M&As as exogenous shocks to the stock of acquirer banks' technology knowledge. Panel A presents the standard DiD reesults where *Treated* and *Post* dummies variables are defined in Section D. We include the same set of controls as in the baseline. We control for loan type fixed effects, loan purpose fixed effects, borrower industry fixed effects, lender fixed effects and year fixed effects across all specifications. Panel B presents the dynamic DiD results where we replace the single *Post* dummy variable with a series of indicators $\{D_j\}$ and D_j takes the value of one if the loan is issued in the j-th year after the event year, and zero otherwise. Definitions of other variables are provided in Table A1 in the Appendix. Numbers in parentheses are heteroskedasticity-robust standard errors clustered at the lender and year levels. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Standard Difference-in-Differences Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Post × Treated	-0.138***	-0.137**	-0.138**	-0.135**	-0.136**	-0.135**
	(0.049)	(0.049)	(0.052)	(0.052)	(0.055)	(0.054)
Post	0.010	0.011	0.011	0.011	0.011	0.012
	(0.017)	(0.017)	(0.017)	(0.018)	(0.017)	(0.017)
Treated	-0.047	-0.044	-0.032	-0.036	-0.025	-0.023
	(0.066)	(0.066)	(0.069)	(0.069)	(0.072)	(0.072)
Segment Similarity		0.173		0.191		0.176
		(0.442)		(0.425)		(0.432)
Borrower Product Market HHI			-0.183***		-0.178***	-0.177***
			(0.039)		(0.041)	(0.041)
Borrower Patent Stock				-0.009	-0.008	-0.009
				(0.013)	(0.013)	(0.013)
Borrower Patent Value				-0.003**	-0.003**	-0.003**
				(0.001)	(0.001)	(0.001)
Prior Relationship	-0.008	-0.008	-0.015	-0.009	-0.015	-0.015
	(0.069)	(0.069)	(0.067)	(0.070)	(0.068)	(0.068)
Borrower Size	-0.158***	-0.159***	-0.163***	-0.144***	-0.148***	-0.149***
	(0.023)	(0.023)	(0.022)	(0.021)	(0.020)	(0.021)
Borrower Leverage	0.543***	0.544***	0.555***	0.523***	0.535***	0.535***
	(0.116)	(0.115)	(0.111)	(0.106)	(0.103)	(0.102)
Borrower Z-score	-5.451***	-5.388***	-5.217***	-5.663***	-5.494***	-5.433***
	(1.810)	(1.818)	(1.754)	(1.814)	(1.757)	(1.756)
Borrower Profitability	-1.382***	-1.383***	-1.386***	-1.317***	-1.323***	-1.323***
	(0.263)	(0.262)	(0.269)	(0.259)	(0.265)	(0.264)
Borrower Market-to-Book	-1.104***	-1.102***	-1.021***	-1.013***	-0.938***	-0.936***
	(0.189)	(0.200)	(0.233)	(0.208)	(0.246)	(0.250)
Borrower Cash	0.458***	0.459***	0.401**	0.481***	0.424***	0.425***
	(0.150)	(0.150)	(0.143)	(0.146)	(0.138)	(0.138)
Borrower Has Credit Rating	0.021	0.021	0.014	0.016	0.009	0.009
	(0.036)	(0.036)	(0.037)	(0.037)	(0.037)	(0.037)
ln(Loan Size)	-0.066***	-0.065***	-0.066***	-0.067***	-0.068***	-0.067***
	(0.020)	(0.020)	(0.020)	(0.019)	(0.019)	(0.019)
ln(Loan Maturity)	0.025	0.025	0.025	0.022	0.022	0.022
	(0.028)	(0.028)	(0.027)	(0.028)	(0.027)	(0.027)
Loan Secured	0.469***	0.469***	0.465***	0.470***	0.466***	0.466***
	(0.055)	(0.055)	(0.054)	(0.055)	(0.054)	(0.054)
Loan Type and Purpose Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Lender Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,170	4,170	4,170	4,170	4,170	4,170
Adjusted R^2	0.722	0.722	0.724	0.723	0.725	0.725

Table 9: **Continued**

Panel B: Dynamic Difference-in-Differences Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
D_{-1} × Treated	-0.068	-0.069	-0.063	-0.064	-0.058	-0.059
	(0.081)	(0.080)	(0.083)	(0.088)	(0.091)	(0.091)
D_0 × Treated	0.009	0.007	-0.005	0.003	-0.008	-0.010
	(0.061)	(0.064)	(0.061)	(0.069)	(0.065)	(0.070)
D_1 × Treated	-0.132*	-0.134*	-0.142*	-0.138*	-0.144*	-0.147*
	(0.071)	(0.072)	(0.069)	(0.074)	(0.071)	(0.072)
D_2 × Treated	-0.138	-0.139	-0.151*	-0.145	-0.156*	-0.158*
	(0.091)	(0.090)	(0.085)	(0.087)	(0.082)	(0.082)
D_{-1}	0.012	0.012	0.007	0.015	0.010	0.010
	(0.023)	(0.024)	(0.024)	(0.023)	(0.023)	(0.023)
D_0	0.019	0.019	0.018	0.022	0.020	0.020
	(0.020)	(0.021)	(0.021)	(0.021)	(0.021)	(0.022)
D_1	0.012	0.012	0.008	0.014	0.009	0.010
	(0.022)	(0.023)	(0.022)	(0.023)	(0.023)	(0.023)
D_2	0.020	0.020	0.020	0.023	0.022	0.023
	(0.027)	(0.028)	(0.027)	(0.028)	(0.028)	(0.029)
Treated	-0.015	-0.011	-0.007	-0.006	-0.003	0.002
	(0.076)	(0.076)	(0.080)	(0.079)	(0.083)	(0.083)
Segment Similarity		0.277		0.307		0.295
		(0.467)		(0.451)		(0.453)
Borrower Product Market HHI			-0.177***		-0.172***	-0.172***
			(0.038)		(0.039)	(0.039)
Borrower Patent Stock				-0.011	-0.010	-0.010
				(0.011)	(0.011)	(0.011)
Borrower Patent Value				-0.002*	-0.002	-0.002
				(0.001)	(0.001)	(0.001)
Prior Relationship	-0.051	-0.050	-0.058	-0.050	-0.058	-0.057
	(0.065)	(0.065)	(0.063)	(0.067)	(0.066)	(0.066)
Loan Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type and Purpose Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Lender Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,310	5,310	5,310	5,310	5,310	5,310
Adjusted R^2	0.713	0.713	0.715	0.714	0.716	0.716

Table 10: **Heterogeneous Effects of Borrower Technology Similarity: Banks**

Table 10 examines the heterogeneous effects of borrower technology similarity on loan spread for different banks. Specifically, we estimate the model as in column (6) of Table 2 and additionally include bank characteristics and their interaction with technology similarity. In all specifications, we control for bank-borrower prior lending relationship, borrower characteristics, loan characteristics, and fixed effects for loan type, loan purpose, borrower industry – year, and lender. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are heteroskedasticity-robust standard errors clustered at the borrower level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Technology Similarity	-2.669***	-1.846***	-0.547***
	(0.612)	(0.407)	(0.152)
Technology Similarity × Bank Size	0.182***		
	(0.047)		
Technology Similarity × Bank Tier 1 Capital Ratio		0.147***	
		(0.034)	
Technology Similarity × Bank Loan-to-Deposit Shortfall			-1.772**
			(0.783)
Bank Size	-0.074***		
	(0.017)		
Bank Tier 1 Capital Ratio		-0.006	
		(0.004)	
Bank Loan-to-Deposit Shortfall			0.051
			(0.079)
Segment Similarity	0.288***	0.241**	0.306***
	(0.098)	(0.106)	(0.099)
Borrower Product Market HHI	-0.116***	-0.114***	-0.117***
	(0.021)	(0.021)	(0.021)
Borrower Patent Stock	-0.000	-0.000	0.000
	(0.001)	(0.001)	(0.001)
Borrower Patent Value	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Prior Relationship	-0.015	-0.022*	-0.015
	(0.011)	(0.011)	(0.011)
Borrower Size	-0.091***	-0.088***	-0.091***
	(0.006)	(0.006)	(0.006)
Borrower Leverage	0.610***	0.596***	0.610***
	(0.028)	(0.028)	(0.028)
Borrower Z-score	-1.795***	-1.996***	-1.831***
	(0.481)	(0.492)	(0.482)
Borrower Profitability	-1.076***	-1.086***	-1.076***
	(0.065)	(0.068)	(0.066)
Borrower Market-to-Book	-0.273***	-0.269***	-0.269***
	(0.074)	(0.074)	(0.074)
Borrower Cash	0.056	0.060	0.062
	(0.052)	(0.053)	(0.052)
Borrower Has Credit Rating	0.042***	0.044***	0.042***
	(0.012)	(0.012)	(0.012)
ln(Loan Size)	-0.092***	-0.093***	-0.093***
	(0.005)	(0.005)	(0.005)
ln(Loan Maturity)	0.003	0.019**	0.003
	(0.008)	(0.008)	(0.008)
Loan Secured	0.368***	0.363***	0.369***
	(0.010)	(0.011)	(0.010)
Loan Type and Purpose Fixed Effects	Yes	Yes	Yes
Borrower Industry × Year Fixed Effects	Yes	Yes	Yes
Lender Fixed Effects	Yes	Yes	Yes
Observations	30,485	28,734	30,485
Adjusted R^2	0.639	0.645	0.639

Table 11: **Heterogeneous Effects of Borrower Technology Similarity: Borrowers**

Table 11 examines the heterogeneous effects of borrower technology similarity on loan spread for different borrowers. Specifically, we estimate the model as in column (6) of Table 2 and additionally include the interaction of technology similarity and three borrower characteristics: Altman's Z-score, leverage, and profitability, respectively. In all specifications, we control for bank-borrower prior lending relationship, borrower characteristics, loan characteristics, and fixed effects for loan type, loan purpose, borrower industry – year, and lender. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are heteroskedasticity-robust standard errors clustered at the borrower level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Technology Similarity	-0.157	-0.534***	0.188
	(0.129)	(0.156)	(0.158)
Technology Similarity × Borrower Z-score	-17.190***		
	(5.990)		
Technology Similarity × Borrower Leverage		0.905**	
		(0.413)	
Technology Similarity × Borrower Profitability			-4.382***
			(0.982)
Borrower Z-score	-8.491***		
	(0.431)		
Borrower Leverage		0.580***	
		(0.028)	
Borrower Profitability			-1.110***
			(0.058)
Segment Similarity	0.239**	0.273***	0.266***
	(0.095)	(0.095)	(0.095)
Borrower Product Market HHI	-0.090***	-0.131***	-0.101***
	(0.020)	(0.020)	(0.020)
Borrower Patent Stock	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Borrower Patent Value	-0.002***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Prior Relationship	-0.022**	-0.037***	-0.022**
	(0.011)	(0.011)	(0.011)
Borrower Size	-0.077***	-0.075***	-0.082***
	(0.006)	(0.005)	(0.006)
Borrower Market-to-Book	-0.429***	-0.479***	-0.325***
	(0.074)	(0.081)	(0.073)
Borrower Cash	-0.171***	0.037	-0.257***
	(0.048)	(0.051)	(0.048)
Borrower Has Credit Rating	0.058***	0.031***	0.081***
	(0.012)	(0.012)	(0.012)
ln(Loan Size)	-0.101***	-0.110***	-0.097***
	(0.005)	(0.004)	(0.005)
ln(Loan Maturity)	0.011	0.002	0.015**
	(0.007)	(0.007)	(0.007)
Loan Secured	0.422***	0.417***	0.425***
	(0.010)	(0.010)	(0.010)
Loan Type and Purpose Fixed Effects	Yes	Yes	Yes
Borrower Industry × Year Fixed Effects	Yes	Yes	Yes
Lender Fixed Effects	Yes	Yes	Yes
Observations	36,166	36,166	36,166
Adjusted R^2	0.638	0.639	0.638

Table 12: **Borrower Technology Similarity and Technological Obsolescence**

Table 12 examines the heterogeneous effects of borrower technology similarity on loan spread conditional on borrowers' technological obsolescence as in Ma (2021). Specifically, columns (1) and (2) report the results based on the low Technological Obsolescence dummy that equals to 1 if the borrowers' Technological Obsolescence is below the annual median. Columns (3) and (4) alternatively use the annual decile rank of borrowers' technological obsolescence. ω is the window length used in computing technological obsolescence as in Ma (2021). In all specifications, we control for bank-borrower prior lending relationship, borrower characteristics, loan characteristics, and fixed effects for loan type, loan purpose, borrower industry – year, and lender. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are heteroskedasticity-robust standard errors clustered at the borrower level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Technology Similarity	0.138	0.153	-0.760***	-0.731***
	(0.192)	(0.191)	(0.272)	(0.273)
Technology Similarity × Low Technology Obsolescence ($\omega = 5$)	-0.527**	-0.522**		
	(0.221)	(0.222)		
Technology Similarity × Technology Obsolescence Rank ($\omega = 5$)			0.116***	0.114***
			(0.041)	(0.041)
Low Technology Obsolescence ($\omega = 5$)	0.037	0.036		
	(0.024)	(0.024)		
Technology Obsolescence Rank ($\omega = 5$)			-0.006	-0.005
			(0.004)	(0.004)
Borrower Patent Stock		-0.001		-0.001
		(0.001)		(0.001)
Borrower Patent Value		-0.001***		-0.001***
		(0.000)		(0.000)
Segment Similarity	0.329	0.328	0.334	0.333
	(0.248)	(0.248)	(0.249)	(0.249)
Borrower Product Market HHI	-0.086**	-0.088**	-0.086**	-0.089**
	(0.035)	(0.035)	(0.035)	(0.035)
Prior Relationship	-0.071***	-0.072***	-0.070***	-0.071***
	(0.023)	(0.023)	(0.023)	(0.023)
Borrower Size	-0.072***	-0.062***	-0.072***	-0.062***
	(0.011)	(0.011)	(0.011)	(0.011)
Borrower Leverage	0.694***	0.675***	0.690***	0.671***
	(0.063)	(0.063)	(0.063)	(0.063)
Borrower Z-score	-2.578**	-2.800***	-2.633***	-2.854***
	(1.013)	(1.013)	(1.017)	(1.017)
Borrower Profitability	-1.760***	-1.692***	-1.756***	-1.688***
	(0.160)	(0.159)	(0.160)	(0.159)
Borrower Market-to-Book	-0.505***	-0.445***	-0.500***	-0.440***
	(0.131)	(0.126)	(0.131)	(0.126)
Borrower Cash	0.263**	0.274**	0.258**	0.270**
	(0.117)	(0.115)	(0.117)	(0.115)
Borrower Has Credit Rating	-0.002	-0.009	-0.001	-0.009
	(0.023)	(0.023)	(0.023)	(0.023)
ln(Loan Size)	-0.110***	-0.110***	-0.110***	-0.110***
	(0.010)	(0.010)	(0.010)	(0.010)
ln(Loan Maturity)	0.071***	0.068***	0.071***	0.068***
	(0.013)	(0.013)	(0.013)	(0.013)
Loan Secured	0.389***	0.392***	0.389***	0.392***
	(0.021)	(0.021)	(0.021)	(0.021)
Loan Type and Purpose Fixed Effects	Yes	Yes	Yes	Yes
Borrower Industry × Year Fixed Effects	Yes	Yes	Yes	Yes
Lender Fixed Effects	Yes	Yes	Yes	Yes
Observations	10,311	10,311	10,311	10,311
Adjusted R^2	0.723	0.724	0.723	0.724

Appendix

Table A1: **Variable Definition**

Variable	Definition	Source
Bank-borrower level variables		
Technology Similarity	The cosine similarity of the technology profiles between the current borrower and banks' lending portfolios over the past five years	USPTO
Segment Similarity	The cosine similarity of the product market segments between the current borrower and banks' prior lending portfolios	Compustat Segment
Borrower In Bank Top Industries	A dummy variable equals to one if the borrower is within the bank's top-five 2-digit SIC lending industries by total loan volume each year	DealScan
Prior Relationship	Bharath et al. (2011) relationship lending measure: the total amount of loan by the lead bank to the current borrower in the last five years divided by the total amount of loans by the borrower in the last five years	DealScan
Geographic Distance	The distance in kilometre (km) between the borrower and the bank based on their headquarters' ZIP codes.	Compustat
Loan level variables		
Loan Spread	The all-in-drawn loan spread measured in basis points	DealScan
Loan Size	Total amount of a loan facility in millions of US dollars	DealScan
Maturity	Total number of months to maturity of a loan facility	DealScan
Loan Secured	A dummy variable equals to one if the loan facility is secured	DealScan
Total Bank Loan Cost	Total bank loan cost constructed by Berg et al. (2016) including all fees charged by lenders	DealScan & Berg et al. (2016)
Borrower level variables		
Borrower Product Market HHI	The Hoberg and Phillips (2016) 10-K Text-based Network (TNIC) Industry Herfindahl-Hirschman Index	Hoberg-Phillips Data Library
Borrower Product Market Similarity	The Hoberg and Phillips (2016) 10-K Text-based Network (TNIC) Industry total similarity of each firm to the product market, calculated by firm-by-firm pairwise cosine similarity	Hoberg-Phillips Data Library
Borrower Product Market Fluidity	The Hoberg et al. (2014) 10-K based product market fluidity measuring how intensively the product market around a firm is changing in each year	Hoberg-Phillips Data Library
Borrower Patent Stock	The borrower patent stock created by capitalizing the number of granted patents in the last five years with 20% depreciation rate as in Chava et al. (2017)	USPTO
Borrower Patent Value	The borrower average patent value computed as the total Kogan et al. (2017) patent value at the firm level scaled by the number of patents granted	USPTO & Kogan et al. (2017)
Borrower Size	The natural logarithm of borrower total assets (AT)	Compustat
Borrower Leverage	The borrower financial leverage measured as the ratio of total debt (sum of long-term debt (DLTT) and debt in current liabilities (DLC)) to total assets (AT)	Compustat
Borrower Z-score	The borrower modified Altman's Z-score = (1.2×working capital (WCAP) + 1.4×retained earnings (RE) + 3.3×pretax-income (PI) + 0.999×total sales (SALE))/total assets (AT). We follow Hasan et al. (2014) and ignore the ratio of market value of equity to book value of total debt, since we control for a similar term borrower market-to-book ratio in our regressions	Compustat
Borrower Profitability	The borrower earnings before interest, taxes, depreciation, and amortization (EBITDA) scaled by total assets (AT)	Compustat
Borrower Market-to-Book	The borrower market value of equity scaled by the book value of equity ((PRCC_F×CSHO)/CEQ)	Compustat
Borrower Cash	The borrower cash and marketable securities (CHE) scaled by borrowers' total assets (AT)	Compustat
Borrower Has Credit Rating	A dummy variable equals to 1 if the borrower has the public credit rating	Compustat

Table A1: **Continued**

Variable	Definition	Source
Borrower Bank-Dependent	The Schwert (2018) borrower bank-dependent indicator: a dummy variable equals to 1 if the borrower has no public credit rating	Compustat
Borrower Default Probability	The probability of default estimated using the Bharath and Shumway (2008) naive distance-to-default measure	Compustat & CRSP
Low Technological Obsolescence	A dummy variable equals 1 if a borrower's technological obsolescence as in Ma (2021) is below the annual median.	USPTO
Technological Obsolescence Rank	The annual decile rank of a borrower's technological obsolescence as in Ma (2021).	USPTO
Bank-level variables		
Bank Size	The natural logarithm of bank's total asset (AT)	Compustat Bank
Bank Capital	The Schwert (2018) bank capital ratio: market capitalization/quasi-market assets, where quasi-market assets is defined as book assets minus the book value of common equity, plus the market capitalization of common equity	Compustat Bank
Bank Tier 1 Capital Ratio	Bank risk-adjusted capital ratio - Tier 1	Compustat Bank
Bank Deposits	Bank deposits normalized by total assets	Compustat Bank
Bank Non-Deposit Leverage	The Gropp and Heider (2010) bank non-deposit leverage: the ratio of bank debt, excluding deposit, to bank assets = debt in current liabilities (DLCQ) + long-term debt (DLTTQ) / total assets (ATQ)	Compustat Bank
Bank Loan-to-Deposit Shortfall	The Acharya and Mora (2015) loan-to-deposit shortfall: [total loans (LNTAL) - deposits (DPTC)]/total assets (AT)	Compustat Bank

Table A2: **Borrower Technology Similarity Using Alternative Time Windows**

Table A2 reports the robustness check of the baseline results that measures borrower technology similarity using banks' past 1-year, 3-year, 7-year and all history lending portfolios. The dependent variable is the natural logarithm of loan spreads. Additionally, we construct the segment similarity using the corresponding alternative time window. In all specifications, we control for bank-borrower prior lending relationship, borrower characteristics, loan characteristics, and fixed effects for loan type, loan purpose, borrower industry – year, and lender. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are heteroskedasticity-robust standard errors clustered at the borrower level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	1Y Window		3Y Window		7Y Window		All History	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Technology Similarity	-0.158**	-0.130**	-0.236***	-0.198***	-0.332***	-0.274***	-0.438***	-0.366***
	(0.062)	(0.060)	(0.077)	(0.075)	(0.090)	(0.088)	(0.104)	(0.101)
Segment Similarity	0.103		0.162**		0.272***		0.306***	
	(0.064)		(0.079)		(0.092)		(0.098)	
Borrower Product Market HHI		-0.114***		-0.113***		-0.113***		-0.111***
		(0.020)		(0.020)		(0.020)		(0.020)
Borrower Patent Stock	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Borrower Patent Value	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Prior Relationship	-0.023**	-0.023**	-0.024**	-0.022**	-0.024**	-0.022**	-0.024**	-0.022**
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Borrower Size	-0.081***	-0.084***	-0.081***	-0.084***	-0.080***	-0.083***	-0.079***	-0.082***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Borrower Leverage	0.558***	0.566***	0.557***	0.565***	0.555***	0.564***	0.554***	0.563***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Borrower Z-score	-2.049***	-1.875***	-2.066***	-1.898***	-2.073***	-1.908***	-2.089***	-1.918***
	(0.440)	(0.438)	(0.440)	(0.438)	(0.440)	(0.437)	(0.439)	(0.437)
Borrower Profitability	-1.110***	-1.113***	-1.110***	-1.113***	-1.110***	-1.113***	-1.109***	-1.113***
	(0.063)	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)
Borrower Market-to-Book	-0.286***	-0.276***	-0.284***	-0.275***	-0.282***	-0.275***	-0.284***	-0.277***
	(0.071)	(0.070)	(0.071)	(0.070)	(0.071)	(0.070)	(0.071)	(0.070)
Borrower Cash	0.091*	0.060	0.092*	0.063	0.094*	0.064	0.095*	0.065
	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.048)
Borrower Has Credit Rating	0.035***	0.035***	0.035***	0.035***	0.035***	0.035***	0.036***	0.035***
	(0.012)	(0.011)	(0.012)	(0.011)	(0.012)	(0.011)	(0.012)	(0.011)
ln(Loan Size)	-0.097***	-0.098***	-0.097***	-0.097***	-0.097***	-0.097***	-0.097***	-0.097***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
ln(Loan Maturity)	0.014*	0.014**	0.014*	0.014**	0.014*	0.014**	0.014*	0.014**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Loan Secured	0.386***	0.384***	0.385***	0.384***	0.385***	0.383***	0.384***	0.383***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Loan Type and Purpose Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Industry × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,166	36,166	36,166	36,166	36,166	36,166	36,166	36,166
Adjusted R^2	0.654	0.655	0.654	0.655	0.655	0.655	0.655	0.656

Table A3: **Borrower Technology Similarity and Total Loan Cost**

Table A3 reports the results of regressing the natural logarithm of total loan costs from Berg et al. (2016) on borrower technology similarity. Specifically, column (1) controls for the borrower's segment similarity with bank's prior borrowers. Columns (2) through (4) control for competition faced by the borrower using three of Hoberg and Phillips (2016) product market competition measures, respectively. Columns (5) to (7) additionally control for the borrower's patent stock. In all specifications, we control for the bank-borrower prior lending relationship, borrower characteristics, loan characteristics, and fixed effects for loan type, loan purpose, borrower industry – year, and lender. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are heteroskedasticity-robust standard errors clustered at the borrower level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Technology Similarity	-0.433***	-0.454***	-0.406***	-0.413***	-0.387***	-0.385***	-0.394***	-0.359***
	(0.118)	(0.121)	(0.117)	(0.118)	(0.118)	(0.121)	(0.123)	(0.122)
Segment Similarity		0.128				0.120	0.125	0.099
		(0.123)				(0.121)	(0.122)	(0.121)
Borrower Product Market HHI			-0.123***			-0.123***		
			(0.023)			(0.023)		
Borrower Product Market Similarity				0.007***			0.007***	
				(0.002)			(0.002)	
Borrower Product Market Fluidity					0.015***			0.015***
					(0.002)			(0.002)
Borrower Patent Stock						-0.000	-0.000	-0.001
						(0.003)	(0.003)	(0.003)
Borrower Patent Value						-0.001**	-0.001**	-0.001***
						(0.000)	(0.000)	(0.000)
Prior Relationship	-0.019*	-0.021*	-0.020*	-0.020*	-0.020*	-0.023**	-0.023*	-0.022*
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Borrower Size	-0.096***	-0.096***	-0.100***	-0.098***	-0.101***	-0.097***	-0.095***	-0.098***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Borrower Leverage	0.678***	0.678***	0.689***	0.683***	0.684***	0.684***	0.677***	0.678***
	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)
Borrower Z-score	-3.929***	-3.921***	-3.761***	-3.679***	-3.212***	-3.793***	-3.711***	-3.239***
	(0.562)	(0.562)	(0.562)	(0.561)	(0.566)	(0.561)	(0.560)	(0.566)
Borrower Profitability	-1.171***	-1.171***	-1.173***	-1.170***	-1.186***	-1.156***	-1.154***	-1.169***
	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)
Borrower Market-to-Book	-0.578***	-0.579***	-0.558***	-0.596***	-0.607***	-0.522***	-0.561***	-0.570***
	(0.125)	(0.125)	(0.124)	(0.124)	(0.124)	(0.123)	(0.123)	(0.123)
Borrower Cash	0.005	0.004	-0.030	-0.020	-0.056	-0.027	-0.017	-0.053
	(0.067)	(0.067)	(0.066)	(0.067)	(0.066)	(0.066)	(0.066)	(0.066)
Borrower Has Credit Rating	-0.022	-0.022	-0.022	-0.022	-0.022	-0.023*	-0.023*	-0.024*
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
ln(Loan Size)	-0.042***	-0.042***	-0.043***	-0.043***	-0.042***	-0.043***	-0.043***	-0.042***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
ln(Loan Maturity)	-0.208***	-0.208***	-0.207***	-0.207***	-0.207***	-0.209***	-0.209***	-0.209***
	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
Loan Secured	0.509***	0.509***	0.506***	0.507***	0.502***	0.506***	0.507***	0.502***
	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.012)	(0.012)	(0.013)
Loan Type and Purpose Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Industry × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,469	17,469	17,469	17,469	17,469	17,469	17,469	17,469
Adjusted R^2	0.804	0.804	0.805	0.805	0.806	0.805	0.805	0.806

Table A4: **Alternative Industry Definition**

Table A4 reports the results of regressing the natural logarithm of all-in-drawn loan spreads on the borrower technology similarity measure using alternative industry definitions. Specifically, Panel A use the Fama-French 48 industry classification. Columns (1) to (4) report the results controlling for industry–year fixed effects. Columns (5) to (8) control for borrower industry–lender–year fixed effects. Panel B employs Hoberg and Phillips (2016) 10-K text-based fixed industries with 100 classifications. In all specifications, we control for borrower characteristics, loan-level characteristics, bank-borrower prior lending relationship, borrower characteristics, loan characteristics, and fixed effects for loan type and loan purpose. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are heteroskedasticity-robust standard errors clustered at the borrower level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Fama-French 48 Industry (FF48)								
Technology Similarity	-0.294***	-0.242***	-0.258***	-0.223**	-0.347***	-0.300**	-0.319***	-0.297**
	(0.094)	(0.092)	(0.093)	(0.092)	(0.125)	(0.121)	(0.124)	(0.122)
Segment Similarity	0.166*				0.143			
	(0.087)				(0.148)			
Borrower Product Market HHI		-0.105***				-0.116***		
		(0.019)				(0.024)		
Borrower Product Market Similarity			0.005***				0.004**	
			(0.001)				(0.002)	
Borrower Product Market Fluidity				0.015***				0.013***
				(0.002)				(0.002)
Borrower-level and Loan-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type and Purpose Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FF48 Industry × Year Fixed Effects	Yes	Yes	Yes	Yes				
Lender Fixed Effects	Yes	Yes	Yes	Yes				
Lender × FF48 Industry × Year Fixed Effects					Yes	Yes	Yes	Yes
Observations	36,049	36,049	36,049	36,049	32,117	32,117	32,117	32,117
Adj. R-squared	0.655	0.655	0.655	0.657	0.730	0.731	0.731	0.732
Panel B: Text-based Fixed Industry 100 Classifications (FIC100)								
Technology Similarity	-0.330***	-0.281***	-0.293***	-0.270***	-0.393***	-0.354***	-0.375***	-0.349***
	(0.094)	(0.092)	(0.093)	(0.092)	(0.134)	(0.132)	(0.133)	(0.131)
Segment Similarity	0.196**				0.051			
	(0.090)				(0.162)			
Borrower Product Market HHI		-0.095***				-0.123***		
		(0.020)				(0.027)		
Borrower Product Market Similarity			0.004**				0.003*	
			(0.001)				(0.002)	
Borrower Product Market Fluidity				0.015***				0.015***
				(0.002)				(0.002)
Borrower-level and Loan-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type and Purpose Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FIC100 Industry × Year Fixed Effects	Yes	Yes	Yes	Yes				
Lender Fixed Effects	Yes	Yes	Yes	Yes				
Lender × FIC100 Industry × Year Fixed Effects					Yes	Yes	Yes	Yes
Observations	35,935	35,935	35,935	35,935	30,592	30,592	30,592	30,592
Adjusted R^2	0.662	0.662	0.662	0.664	0.747	0.747	0.747	0.748

Table A5: **Alternative Borrower Technology Similarity Measure Controlling for Time-varying Bank Industry Specialization**

Table A5 reports the results of regressing the natural logarithm of all-in-drawn loan spreads on the alternative technology similarity measure calculated as the pairwise similarity between the borrower and the aggregate patent portfolio of the bank's recent borrowers within the 5-year window. Specifically, column (1) reports the baseline result. Column (2) controls for the borrower's segment similarity with bank's prior borrowers. Columns (3) through (5) control for the competition faced by the borrower using three of Hoberg and Phillips (2016) product market competition measures, respectively. Columns (6) to (8) additionally control for the borrower's patent value and patent stock, as well as the segment similarity. In all specifications, we control for bank-borrower prior lending relationship, borrower characteristics, loan characteristics, and fixed effects for loan type, loan purpose, borrower industry–lender–year. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are heteroskedasticity-robust standard errors clustered at the borrower level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Technology Similarity (Portfolio)	-0.150***	-0.154***	-0.143***	-0.146***	-0.137***	-0.112***	-0.114***	-0.103**
	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.043)	(0.043)
Segment Similarity (Portfolio)		0.102				0.088	0.095	0.062
		(0.066)				(0.066)	(0.066)	(0.066)
Borrower Product Market HHI			-0.151***			-0.149***		
			(0.025)			(0.025)		
Borrower Product Market Similarity				0.004***			0.004***	
				(0.002)			(0.002)	
Borrower Product Market Fluidity					0.016***			0.016***
					(0.002)			(0.002)
Borrower Patent Stock						-0.001	-0.001	-0.001
						(0.001)	(0.001)	(0.001)
Borrower Patent Value						-0.001***	-0.001***	-0.001***
						(0.000)	(0.000)	(0.000)
Prior Relationship	-0.046***	-0.049***	-0.047***	-0.047***	-0.046***	-0.051***	-0.051***	-0.050***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Borrower Size	-0.093***	-0.093***	-0.097***	-0.093***	-0.097***	-0.091***	-0.088***	-0.091***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Borrower Leverage	0.677***	0.678***	0.685***	0.679***	0.678***	0.672***	0.666***	0.664***
	(0.033)	(0.033)	(0.033)	(0.033)	(0.032)	(0.032)	(0.033)	(0.032)
Borrower Z-score	-2.915***	-2.856***	-2.659***	-2.719***	-2.226***	-2.736***	-2.783***	-2.309***
	(0.537)	(0.537)	(0.536)	(0.541)	(0.544)	(0.533)	(0.537)	(0.541)
Borrower Profitability	-1.184***	-1.188***	-1.187***	-1.187***	-1.192***	-1.159***	-1.159***	-1.163***
	(0.083)	(0.082)	(0.082)	(0.083)	(0.083)	(0.081)	(0.082)	(0.081)
Borrower Market-to-Book	-0.382***	-0.383***	-0.376***	-0.391***	-0.392***	-0.340***	-0.355***	-0.354***
	(0.087)	(0.087)	(0.086)	(0.088)	(0.089)	(0.084)	(0.085)	(0.086)
Borrower Cash	0.163**	0.158**	0.123*	0.147**	0.103	0.121*	0.144**	0.101
	(0.064)	(0.064)	(0.063)	(0.064)	(0.063)	(0.063)	(0.063)	(0.063)
ln(Loan Size)	-0.080***	-0.080***	-0.081***	-0.081***	-0.081***	-0.081***	-0.081***	-0.081***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
ln(Loan Maturity)	0.034***	0.035***	0.034***	0.035***	0.035***	0.033***	0.033***	0.033***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Loan Secured	0.354***	0.354***	0.351***	0.353***	0.349***	0.351***	0.353***	0.349***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Loan Type and Purpose Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender × Borrower Industry × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31,578	31,578	31,578	31,578	31,578	31,578	31,578	31,578
Adjusted R^2	0.729	0.729	0.730	0.729	0.731	0.731	0.730	0.732

Table A6: **Maximum Pairwise Borrower Technology Similarity Controlling for Time-varying Bank Industry Specialization**

Table A6 reports the results of regressing the natural logarithm of all-in-drawn loan spreads on the alternative technology similarity measure calculated as the largest pairwise similarity between the borrower and the bank's recent borrowers within the 5-year window, additionally controlling for time-varying bank industry specialization via lender times industry times year fixed effects. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are heteroskedasticity-robust standard errors clustered at the borrower level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Technology Similarity (Maximum)	-0.055***	-0.059***	-0.054***	-0.054***	-0.053***	-0.040**	-0.039**	-0.037**
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Segment Similarity (Maximum)		0.018				0.016	0.018	0.014
		(0.016)				(0.016)	(0.016)	(0.016)
Borrower Product Market HHI			-0.152***			-0.151***		
			(0.025)			(0.026)		
Borrower Product Market Similarity				0.004***			0.005***	
				(0.002)			(0.001)	
Borrower Product Market Fluidity					0.016***			0.016***
					(0.002)			(0.002)
Borrower Patent Stock						-0.001	-0.001	-0.001
						(0.001)	(0.001)	(0.001)
Borrower Patent Value						-0.001***	-0.001***	-0.001***
						(0.000)	(0.000)	(0.000)
Borrower Size	-0.092***	-0.092***	-0.096***	-0.093***	-0.096***	-0.091***	-0.087***	-0.090***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Borrower Leverage	0.679***	0.678***	0.687***	0.681***	0.679***	0.671***	0.665***	0.664***
	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
Borrower Z-score	-2.975***	-2.969***	-2.722***	-2.780***	-2.279***	-2.824***	-2.862***	-2.372***
	(0.540)	(0.540)	(0.539)	(0.544)	(0.547)	(0.536)	(0.541)	(0.544)
Borrower Profitability	-1.181***	-1.181***	-1.184***	-1.184***	-1.190***	-1.155***	-1.155***	-1.160***
	(0.083)	(0.083)	(0.082)	(0.083)	(0.083)	(0.082)	(0.082)	(0.082)
Borrower Market-to-Book	-0.382***	-0.383***	-0.376***	-0.392***	-0.391***	-0.339***	-0.355***	-0.353***
	(0.087)	(0.087)	(0.086)	(0.088)	(0.089)	(0.084)	(0.085)	(0.086)
Borrower Cash	0.178***	0.179***	0.138**	0.162**	0.118*	0.140**	0.162**	0.118*
	(0.064)	(0.064)	(0.064)	(0.064)	(0.063)	(0.063)	(0.063)	(0.063)
ln(Loan Size)	-0.081***	-0.081***	-0.082***	-0.082***	-0.082***	-0.082***	-0.082***	-0.082***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
ln(Loan Maturity)	0.035***	0.035***	0.035***	0.036***	0.035***	0.033***	0.034***	0.033***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Loan Secured	0.356***	0.356***	0.353***	0.355***	0.351***	0.353***	0.355***	0.351***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Loan Type and Purpose Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Industry × Lender Fixed Effects × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31,578	31,578	31,578	31,578	31,578	31,578	31,578	31,578
Adjusted R^2	0.728	0.728	0.730	0.729	0.730	0.731	0.730	0.731

Table A7: **Placebo Test: Technology Similarity with Future Borrowers**

Table A7 reports the results of regressing the natural logarithm of all-in-drawn loan spreads on the technology similarity of current borrower with future borrowers from five years to ten years after loan origination. Specifically, column (1) reports the baseline result. Column (2) controls for the borrower's segment similarity with bank's prior borrowers. Columns (3) through (5) control for the competition faced by the borrower using three of Hoberg and Phillips (2016) product market competition measures, respectively. Columns (6) to (8) additionally control for the borrower's patent value and patent stock, as well as the segment similarity. In all specifications, we control for bank-borrower prior lending relationship, borrower characteristics, loan characteristics, and fixed effects for loan type, loan purpose, borrower industry – year, and lender. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are heteroskedasticity-robust standard errors clustered at the borrower level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Technology Similarity (Future Borrowers)	-0.161	-0.162	-0.163	-0.159	-0.140	-0.165	-0.161	-0.140
	(0.103)	(0.104)	(0.103)	(0.103)	(0.102)	(0.103)	(0.103)	(0.102)
Segment Similarity (Future Borrowers)		0.038				0.021	0.029	0.013
		(0.232)				(0.229)	(0.230)	(0.232)
Borrower Product Market HHI			-0.107***			-0.110***		
			(0.028)			(0.028)		
Borrower Product Market Similarity				0.003			0.004*	
				(0.002)			(0.002)	
Borrower Product Market Fluidity					0.011***			0.011***
					(0.003)			(0.003)
Borrower Patent Stock						-0.000	-0.000	-0.000
						(0.001)	(0.001)	(0.001)
Borrower Patent Value						-0.001***	-0.001***	-0.001***
						(0.000)	(0.000)	(0.000)
Prior Relationship	-0.049***	-0.049***	-0.049***	-0.049***	-0.048***	-0.049***	-0.050***	-0.048***
	(0.018)	(0.018)	(0.017)	(0.018)	(0.018)	(0.017)	(0.017)	(0.017)
Borrower Size	-0.075***	-0.075***	-0.079***	-0.076***	-0.078***	-0.071***	-0.067***	-0.070***
	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
Borrower Leverage	0.651***	0.651***	0.661***	0.656***	0.662***	0.640***	0.635***	0.641***
	(0.046)	(0.046)	(0.046)	(0.045)	(0.045)	(0.046)	(0.045)	(0.045)
Borrower Z-score	-1.484**	-1.482**	-1.188*	-1.317**	-0.889	-1.355**	-1.441**	-1.027
	(0.663)	(0.662)	(0.665)	(0.671)	(0.688)	(0.659)	(0.663)	(0.681)
Borrower Profitability	-1.336***	-1.336***	-1.344***	-1.340***	-1.352***	-1.298***	-1.294***	-1.306***
	(0.104)	(0.104)	(0.104)	(0.104)	(0.104)	(0.102)	(0.102)	(0.102)
Borrower Market-to-Book	-0.385***	-0.385***	-0.379***	-0.390***	-0.396***	-0.303***	-0.314***	-0.319***
	(0.110)	(0.110)	(0.109)	(0.110)	(0.111)	(0.103)	(0.104)	(0.105)
Borrower Cash	0.036	0.036	-0.004	0.020	-0.014	0.008	0.030	-0.002
	(0.078)	(0.078)	(0.077)	(0.078)	(0.077)	(0.075)	(0.077)	(0.076)
ln(Loan Size)	-0.110***	-0.110***	-0.111***	-0.110***	-0.110***	-0.111***	-0.110***	-0.110***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
ln(Loan Maturity)	0.048***	0.048***	0.048***	0.048***	0.048***	0.045***	0.045***	0.045***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Loan Secured	0.409***	0.409***	0.406***	0.408***	0.405***	0.404***	0.407***	0.404***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Loan Type and Purpose Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Industry × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,108	17,108	17,108	17,108	17,108	17,108	17,108	17,108
Adjusted R^2	0.688	0.688	0.689	0.688	0.689	0.691	0.690	0.691

Table A8: **Information Content of Technology Similarity for Future Borrower Creditworthiness**

Table A8 examines the predictive power of a borrower's technology similarity with its bank's prior borrowers for the difference in their future creditworthiness. Specifically, we regress the future absolute difference of borrower's and bank's prior borrowers' average forward creditworthiness measures on their technology similarity, controlling for their segment similarity and absolute differences across an array of firm characteristics. The dependent variable is measured at year $t+h$ and all independent variables are measured at year t. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are heteroskedasticity-robust standard errors clustered at the borrower level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Absolute Difference ($h=1$):	Z-score	Default Probability	Profitability	Cash Holding
	(1)	(2)	(3)	(4)
Technology Similarity	-0.002	-0.046***	-0.054***	-0.002
	(0.003)	(0.012)	(0.013)	(0.012)
Absolute difference controls	Yes	Yes	Yes	Yes
Industry and Year Fixed Effects	Yes	Yes	Yes	Yes
Lender Fixed Effects	Yes	Yes	Yes	Yes
Observations	33,636	26,040	33,652	33,579
Adjusted R^2	0.160	0.268	0.168	0.129

Absolute Difference ($h=2$):	Z-score	Default Probability	Profitability	Cash Holding
	(1)	(2)	(3)	(4)
Technology Similarity	-0.006*	-0.068***	-0.072***	-0.013
	(0.004)	(0.014)	(0.015)	(0.012)
Absolute difference controls	Yes	Yes	Yes	Yes
Industry and Year Fixed Effects	Yes	Yes	Yes	Yes
Lender Fixed Effects	Yes	Yes	Yes	Yes
Observations	30,750	23,455	30,797	30,660
Adjusted R^2	0.028	0.264	0.070	0.140

Absolute Difference ($h=3$):	Z-score	Default Probability	Profitability	Cash Holding
	(1)	(2)	(3)	(4)
Technology Similarity	-0.006**	-0.069***	-0.057***	-0.024*
	(0.003)	(0.014)	(0.015)	(0.012)
Absolute difference controls	Yes	Yes	Yes	Yes
Industry and Year Fixed Effects	Yes	Yes	Yes	Yes
Lender Fixed Effects	Yes	Yes	Yes	Yes
Observations	27,793	21,081	27,853	27,684
Adjusted R^2	0.142	0.281	0.178	0.126

Absolute Difference ($h=4$):	Z-score	Default Probability	Profitability	Cash Holding
	(1)	(2)	(3)	(4)
Technology Similarity	-0.008**	-0.039**	-0.059***	-0.027**
	(0.003)	(0.018)	(0.016)	(0.013)
Absolute difference controls	Yes	Yes	Yes	Yes
Industry and Year Fixed Effects	Yes	Yes	Yes	Yes
Lender Fixed Effects	Yes	Yes	Yes	Yes
Observations	25,108	18,758	25,174	24,984
Adjusted R^2	0.221	0.274	0.203	0.121

Absolute Difference ($h=5$):	Z-score	Default Probability	Profitability	Cash Holding
	(1)	(2)	(3)	(4)
Technology Similarity	-0.007*	-0.065***	-0.078***	-0.033**
	(0.003)	(0.018)	(0.017)	(0.014)
Absolute difference controls	Yes	Yes	Yes	Yes
Industry and Year Fixed Effects	Yes	Yes	Yes	Yes
Lender Fixed Effects	Yes	Yes	Yes	Yes
Observations	22,616	16,922	22,690	22,475
Adjusted R^2	0.115	0.283	0.147	0.119

Table A9: **List of Bank Mergers and Acquisitions (M&A) Events**

Table A9 lists the M&A events used for the difference-in-differences estimations in Table 9.

Event Year	Acquirer Bank	Target Bank
1996	JPMorgan Chase Bank	Chase Manhattan Corp
1996	JPMorgan Chase Bank	Chemical Securities Asia
1996	JPMorgan Chase Bank	Chase Manhattan Bank of Canada
1996	JPMorgan Chase Bank	Chase Manhattan Plc
1996	JPMorgan Chase Bank	Chase Manhattan Asia Ltd
1996	JPMorgan Chase Bank	Chase Manhattan Australia
1996	JPMorgan Chase Bank	Chemical Bank
1996	JPMorgan Chase Bank	Chase Securities
1996	JPMorgan Chase Bank	Chase Manhattan Bank
1996	JPMorgan Chase Bank	Chase Manhattan Australia
1996	JPMorgan Chase Bank	Chase Securities
1996	JPMorgan Chase Bank	Chemical Bank of Canada
1996	JPMorgan Chase Bank	Chemical Bank Australia
1996	JPMorgan Chase Bank	Chase Manhattan Investment Bank Ltd
1996	JPMorgan Chase Bank	Chemical Bank New Jersey NA
1996	JPMorgan Chase Bank	Chase Manhattan Bank of Canada
1996	JPMorgan Chase Bank	Chase Securities Australia
1996	JPMorgan Chase Bank	Chase Manhattan Bank
1997	Bankers Trust Co	BT Alex Brown Inc
1998	Bank of the West	First Hawaiian Bank
1998	Norwest Bank	Foothill Capital Corp
1998	Norwest Bank	Wells Fargo - Texas
1998	Norwest Bank	Wells Fargo Bank Texas NA
1998	Norwest Bank	Foothill Group
1998	Norwest Bank	Wells Fargo Bank
1999	Fleet Bank	Bank Boston Trust Co
1999	Fleet Bank	Michigan National Bank
1999	Fleet Bank	BankBoston NA
1999	Fleet Bank	Bank Boston
1999	Fleet Bank	Shawmut Bank Connecticut
1999	Fleet Bank	BankBoston Corp
1999	Fleet Bank	BankBoston Retail Finance Inc
1999	Fleet Bank	Shawmut Capital Corp
1999	Fleet Bank	BankBoston Capital
1999	Fleet Bank	Bank Boston Singapore
2004	National City Bank	Provident Bank
2005	Zions Bank	Amegy Bank NA
2006	Regions	AmSouth Bank
2008	PNC Bank	National City Bank
2008	PNC Bank	National City Business Credit
2008	Barclays	Lehman Commercial Paper Inc
2015	Royal Bank of Canada	City National Bank
2016	KeyBank	First Niagara Financial Group Inc
2016	KeyBank	First Niagara Bank

Table A10: **Comparison of Treated and Control Banks**

Table A10 shows the t-tests to examine whether the treated and control banks are comparable after propensity score matching on bank size, non-deposit leverage, deposits ratio, and tier 1 capital ratio. Columns (1) and (2) report the mean value of four characteristics for treated and control banks respectively. Column (3) reports the difference. Columns (4) and (5) report the t-statistic and p-value. Column (6) reports the number of observations. Definitions of the variables are provided in Table A1 in the Appendix.

	Mean			t-Test		Observations
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Treated	Control	Difference (1)-(2)	t	$p > \|t\|$	Total
Bank Size	11.782	11.471	0.311	0.530	0.601	120
Bank Non-Deposit Leverage	0.218	0.196	0.022	0.600	0.552	120
Bank Deposits	0.460	0.508	-0.048	-1.170	0.253	120
Bank Tier 1 Capital Ratio	8.892	8.941	-0.049	-0.070	0.944	120

Figure A1: **Average Loan Costs Around the Bank M&A Event Year**

Figure A1 plots the annual average spreads of loans originated by treated and control banks in the sample of the difference-in-differences estimation in Table 9 over the event window.

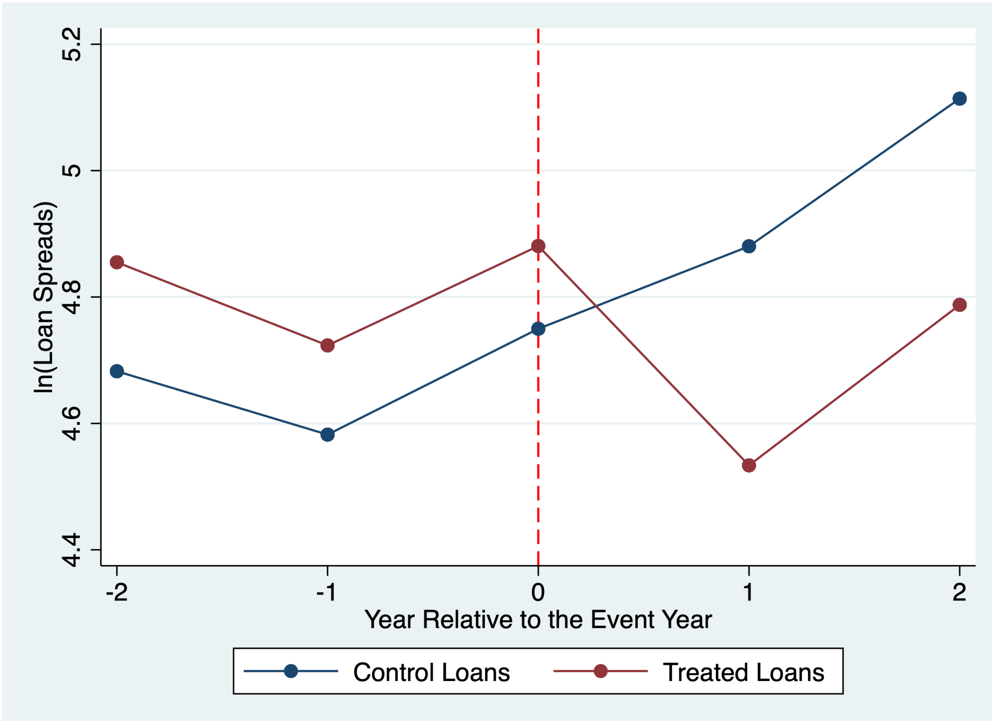

Figure A2: **Treatment Effect Around the Bank M&A Event Year**

Figure A2 shows the coefficient estimates of the interaction of the time dummies and the treated dummy in the dynamic difference-in-differences regression in Table 9. The figure also shows the 90% confidence interval of the coefficient estimates.