Borrower Technology Similarity and Bank Loan Contracting

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Abstract

We find that loans to a borrower sharing similar technologies with the bank's prior borrowers have lower loan spreads, likely due to reduced costs in loan screening and monitoring from bank's accumulated knowledge. Such effect cannot be explained by product market competition, technology value and innovation ability or other firm characteristics. We show that borrower technology similarity is informative about firm creditworthiness. Despite identification challenges, we use a structural bank-borrower matching model to show that the total economic surplus for banks and borrowers can be enhanced by matching banks to borrowers with a high technology similarity to the bank's prior borrowers. This technology similarity also plays an important role in bank's learning-by-lending process.

Keywords: technology similarity, loan contracting, matching model, relationship lending

JEL classifications: G21, G32, O33

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I Introduction

Technology innovation is a key driver of economic growth. In the U.S., corporations take primary responsibility for technology innovations, which already account for about two-thirds of the overall R&D expenditures in 2011 (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 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 problem due to their high opacity and hence requirement for specialized expertise to assess credit risk. To alleviate such problem, greater information disclosure of 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, which may be overlooked by extant studies. 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 bank-borrowing matching economically optimal for banks, borrowers, or both?

We conjecture and empirically find that the technology similarity of a prospective borrower and its bank's prior borrowers in recent years, measured by the average pair-wise technology similarity measure in Jaffe (1986), reduces loan spreads. This effect is ex ante unclear and warrants an empirical study for two reasons. First, borrowers with similar technologies may have greater product market competition as a result of the technologies more likely to be applied in related product markets (e.g., Bereskin et al., 2022). A high technology similarity between the borrowing firm and the bank's prior borrowers could also indicate greater industry segment concentration in the bank's loan portfolio, undermining potential diversification benefits. Second, banks may extract rents based on their accumulated information advantage (e.g., Rajan, 1992) instead of passing on the cost saving from reduced due diligence needed in assessing technology profiles to the borrower. These possible channels could lead to a positive relation between technology similarity and loan spreads, but are not supported by our empirical results. 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, 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 a 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. Our technology similarity measure differs from the technology spillover measure in Bloom et al. (2013) and Qiu and Wan (2015) that captures 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 1989 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 the technology similarity is associated with approximately a 4-basis-point reduction in loan spreads, equivalent to a sizable annual loan costs saving of $170,000 in our sample. 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). These results suggest that the economic value of technology similarity extends beyond its potential correlation with borrower's product market competition, technology profile and innovation ability, and the bank-borrower lending relationship, implying bank cost savings in loan screening and monitoring that are further passed on to the borrowers. Our results have implications for firms too in that innovative borrowers such as those green firms can take this opportunity to reduce their finance costs, which have shown to receive favourable loan recommendations from bankers (Bu et al., 2023). We then show that technology similarity is indeed informative about borrower's creditworthiness in that a higher similarity with the prior borrowers is negatively associated with the absolute difference between their credit risks measured by the Altman's Z-score, Merton (1974) distance to default, and their debt service capabilities measured by profitability and cash holding.

However, establishing a causal link between the borrower's technology similarity with 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 to the technology similarity measure which alters the borrower's technology profile but does not affect the bank-borrower matching or borrower's fundamentals and future business prospects. An instrumental variable regression approach is also empirically challenging to implement as an instrumental variable that correlates with the technology similarity but not with borrower characteristics used in bank's loan pricing is difficult 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 alternatively explore two methods to address the identification challenges and investigate the economic mechanisms underlying the documented negative association between loan spreads and the borrower's technology similarity with the bank's prior borrowers. First and foremost, we use a structural matching model similar to Fox (2017, 2018) and Schwert (2018) to show that such technology similarity is a major determinant of the bank's lending decision and the observed loans are endogenously a result of simultaneous value maximization for banks and borrowers. It allows us to identify drivers of bank-borrower matching assignments in the absence of unobservable non-matching assignments. Specifically, we model firm borrowing and bank lending as respective value maximization with symmetric and offsetting transfer payment such as interests and fees. We can derive an inequality condition for value maximization without the transfer payment, assuming that observed actual bank-borrower matches (loans) yield higher value than unobservable counterfactual loans. As counterfactual loans have no transfer payment data, this condition enables us to perform a semi-parametric estimation for the loan determinants at the bank-borrower level (Schwert, 2018). Our results suggest that the 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 bank's prior borrowers. Lower loan spreads for borrowers with similar technologies to the banks' prior borrowers are optimal for both banks and borrowers.

Our second approach examines the role of technology similarity in bank's learning-by-lending process using a model similar to Farber and Gibbons (1996) and Botsch and Vanasco (2019). In the first stage, we orthogonalize the future borrower technology proxy on the borrower and loan characteristics using the sample of first loans between all bank-borrower pairs. The residuals contain information specific to the borrower but unknown to the borrower at initial loan origination. In the second stage, we regress loan spreads on the residuals and other borrower and loan characteristics. More importantly, we include interactions among the residuals, relationship time and technology similarity. Consistent with Botsch and Vanasco (2019), we find that banks learn from repeated lending. We further find that the technology similarity between a borrower and bank's prior borrowers is unconditionally related to lower loan spreads, but banks exhibit rent extraction to a less extent from the borrower when it has relatively higher technology.

Additionally, we show that the documented negative effect of borrower technology similarity on loan spreads is stronger for smaller, less-capitalized or less-liquid banks, and for borrowers with lower credit risks, leverages or higher profitability. These results are consistent with our conjecture that smaller, less-capitalized or less-liquid banks have more limited resources or risk aversion and hence may value more the accumulated technology knowledge from past lending. Banks also are more willing to cut more loan spreads for high-quality borrowers with lower credit risks, lower leverages or higher profitability.

This study contributes to the literature in three ways. Firstly, we contribute to the burgeoning literature on the implications of technology 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 and shed new light on the economic value of firms' technology innovation.

Secondly, we contribute to the literature on the interplay between financial intermediaries and firm technology innovation. On the one hand, many extant works study 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 the 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 studying the similarity across different borrowers' technology profiles.

Thirdly, our study contributes to the bank loan contracting and relationship lending literature. We highlight the value of accumulating technology knowledge from banks' lending relationships, adding to 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 technology similarity between banks' borrowers.

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 is a key determinant of 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 more, 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 exogenous enhancement of intellectual property protection and patent value result in lower bank loan cost. Mann (2018) identifies that the improved pledgeability of patent 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 cheaper loans.

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 in future bank loan screening and contracting. To the extent that such accumulated knowledge reduces adverse selection and information asymmetry, we expect that banks are more likely to lend to borrowers sharing similar technologies with the prior borrowers. Further, Gustafson et al. (2021) show that bank loan spreads are negatively associated with the value of information and banks' potential monitoring cost. Lending to borrowers sharing similar technologies reduces the monitoring cost. The saved costs from reduced screening and monitoring may then be passed on to the borrower (Bharath et al., 2011). We therefore develop our hypothesis 1 as below:

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 concentration of bank loan portfolios as more borrowers are sharing similar technologies, 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 with the bank's prior borrowers receives lower loan spreads.

Additionally, we consider the role of technology similarity from both bank and borrower sides. We conjecture that smaller banks with less expertise in assessing various firm technology profiles 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 more constrained by their resources and may hence value more the possible 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 with a higher technology similarity, allowing them to capitalize more on their accumulated knowledge. 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 banks' prior borrowers. These borrower have better capabilities in servicing debt, to whom banks may be more wiling to pass on the cost savings due to reduced due diligence needed. We, therefore, form our third hypotheses as below:

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

III Sample and variable construction

This study uses a combination of corporate innovation data from the United States Patent and Trademark Office (USPTO), syndicate loan data from the Thomson Reuters Loan Pricing Corporation (LPC) DealScan database, and firm financial data from Compustat and the Center for Research in Security Prices (CRSP), for the period from January 1984 to December 2020.

A Measuring technology similarity

Consistent with the literature, we measure technology similarity as the pairwise spatial proximity of technological profiles between two entities. Bloom et al. (2013), Qiu and

Wan (2015), and Byun et al. (2021) aggregate all possible technology similarities to 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. In our study, we consider the technology similarity between a borrowing firm and the lending bank's recent borrowers prior to the origination of a new loan, captured by the average pairwise technology similarity measure between the focal borrower and each of the bank's recent borrowers.[1]

Empirically, we compute Jaffe (1986) technology similarity based on firms' patents granted and their technology classifications by the Cooperative Patent Classification (CPC), a classification system jointly developed by the USPTO and European Patent Office (EPO).[2] Specifically, the pairwise technology similarity between a 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:

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

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.[3] The value of each element in the vector T_{it} is strictly within $[0, 1]$, as each element reflects the proportion of a firm's technology profile within a technology class. 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 respective borrowing time τ in the five-year window, i.e., $\tau \in (t-5, t)$, instead of time t, in computing the pairwise technology similarity. Figure 1 provides a graphical illustration.

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

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

[3] 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 3-year and 7-year windows. All of our empirical results still hold if we use the USPTO classification system using data before 2013 (USPTO technology class system was replaced by the newer CPC technology class system in 2013).

Finally, 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:

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

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 bank-borrower 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.[4] Our technology similarity measure also differs from the well-known technology spillover measure (Bloom et al., 2013; Qiu & Wan, 2015) which captures a firm's technology similarity to the whole economy, while we calculate the technology similarity at the bank-firm-year level, representing each bank's technological expertise at each loan origination year towards each borrower.

[Insert Figure 1 about here]

[4]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 prior number of loans or total loan amount.

B Sample and summary statistics

B.1 Data sources

We collect the patent data from the USPTO for the period from 1980 to 2020 to account for the five-year window used 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).[5] Our final sample of patents matched with CRSP/Compustat firms consists of 2,331,801 unique observations. Notably, we use the patent grant date when identifying a firm's patent portfolio.[6] We obtain patents' technology classification data directly from the USPTO PatentsView, which regularly updates patent information including classifications, inventors and organisations.[7] Prior studies employ the United States Patent Classification (USPC) 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.[8]

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.

[5] 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 the maximum accuracy.

[6] 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.

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

[8] 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.

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.[9] 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 1989 to 2020.[10] 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

[9]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.

[10]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.

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 in the analyses by year at the 1^{st} and 99^{th} 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 is 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 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 (loan spreads). The mean (median) of loan spreads is 205.31 basis points (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) 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 select a comparable sample of borrowers to those examined in the literature. For example, the average (median) natural logarithm of the total asset size of borrowers in our sample is 7.07 (7.10) and the average (median) leverage ratio is 0.31 (0.29). 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 0.133, a Tier 1 capital ratio of 9.921, and a loan-to-deposit shortfall of -0.115, comparable with prior studies.

IV Main results

A Baseline model and results

To empirically test whether borrower's technology similarity with bank's prior borrowers reduces loan costs, we start by estimating the following baseline regression:

$$\begin{aligned}\ln(\mathit{Loan\ Spread}_{i,l,t}) = \beta_0 + \beta_1 \mathit{Technology\ Similarity}_{i,l,t} + \beta_2 X_{i,t-1} + \beta_3 \Gamma_{l,t} \\ + \text{Fixed Effects} + \varepsilon_{i,l,t}\end{aligned} \tag{3}$$

where $\mathit{Loan\ Spread}_{i,l,t}$ is the natural logarithm of 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 Altman Z-score, profitability, market-to-book ratio, cash holding and whether it has 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), which may be related to reduced due diligence and monitoring cost and hence lower loan spread. 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.[11] 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.[12]

[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, statistically significant at the 1% level. A one-standard-deviation increase in the borrower technology similarity reduces the loan spread by 4 basis points (bps).[13] Economically, given a sample mean loan size of $425 million, it translates to a sizable annual loan costs saving of $170,000.

B Robustness: concentration, competition and technology value

Further, 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, which implies potentially higher industry concentration for the bank's loan portfolio. We expect and empirically confirm that such higher portfolio concentration to be positively associated with loan spreads. The negative relationship between borrower technology similarity and loan spreads, however, remains statistically

[11] 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.

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

[13] 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 $e^{5.066} - e^{5.066-0.38\times0.06} \approx 4$ basis points.

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).[14] To account for such effect, we control for borrower product market market rivalry using three different measures from Hoberg and 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 favourable loan spreads regardless of its technology similarity with bank's prior borrowers. If technology similarity is then correlated with the firm's technology value,[15] 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 remain 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.

Lastly, in Table 3, 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.

[14]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.

[15]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.

(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.

[Insert Table 3 about here]

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,[16] followed by a discussion of the empirical challenges for identification. We then use a semi-parametric structural matching model similar to Fox (2017, 2018) to show that such technology similarity is a major determinant of bank's lending decision and endogenously a result of bank value maximization. Lastly, we discuss the role of technology similarity in bank's learning-by-lending process using a model similar to Farber and Gibbons (1996) and Botsch and Vanasco (2019).

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

[16] We thank Christoph Herpfer for suggesting this test.

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 by borrower firm.[17]

[Insert Table 4 about here]

Table 4 shows that a higher technology similarity is negatively associated with the absolute difference in borrowers' Altman Z-score, Merton (1974) distance to default, 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 servicing debt, and hence suggest that the information content embedded in the borrower technology similarity is relevant 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 lending to a borrower with similar technologies with its 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 challenging for two reasons. First, an exogenous shock to the observed borrower technology similarity

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

is unlikely. Because the similarity is measured by bank-borrower match and based on the borrowing firm's technology profile and that of the bank's prior borrowers, an ideal shock to the similarity in technology profiles should 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 such as difference-in-differences estimation or instrumental variable regression approach.[18]

To establish that banks do benefit from lending to firms with similar technology profiles with prior borrowers and they willingly cut loan spreads to pass on the cost savings to borrowers, we address the identification challenges using two methods. 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. We then show that technology similarity unconditionally adds value in the bank's process of learning firm-specific characteristics observable

[18]Nevertheless, we conduct a standard difference-in-differences (DiD) estimation exploiting the adoption of the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS) in 1995 as a quasi-natural experiment. TRIPS enhances intellectual property protection and represents an exogenous positive shock to firm technology value, which is expected to increase the value of the bank's accumulated knowledge so that lending to borrowers sharing similar technologies leads to higher cost savings. Using an event window of two years before and after the event year 1995, consistent with Chava et al. (2017), we find that treatment borrowers with above median technology similarity per year receive significantly lower loan spreads compared to control firms in the post-event period, controlling for patent value and product market rivalry. We report the result in Table A2 in the Appendix. To the extent that TRIPS does not materially affect bank-borrower matching and increases the value of the bank's accumulated knowledge from past lending, our results suggest that lending to borrowers with a higher technology similarity with the bank's prior borrowers leads to reduced loan spreads.

only through forming a lending relationship, especially for firms with high technology value.

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, this matching model enables us to identify the drivers of observed bank-borrower matching assignments in the absence of unobservable non-matching assignments, as we as econometricians cannot observe any failed loan applications or any counterfactual matching assignments.

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 maximise 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):[19]

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

where $V = V_b + V_f$, representing the total economic surplus for banks and borrowers (Schwert, 2018). Intuitively, such condition implies that the actual matching assignments should lead to higher total surplus than counterfactual matches.[20] As a result, it shows that the value function is driven by the match characteristics rather than factors specific to banks or borrowers.[21]

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 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.[22] Following Schwert (2018), we restrict the samples to the loans with

[19]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.

[20]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.

[21]All bank and borrower characteristics enter the inequality on both sides and are hence cancelled out. Note that this is also a result of the model considering a subset of all possible matching assignments.

[22]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.

only one lead bank to avoid many-to-many matching complications.[23] 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).[24]

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 the firm B and bank A's prior borrowers) are still known. However, loan characteristics unobservable for counterfactual matches are excluded similarly to Schwert (2018).[25] 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 the borrower. More importantly, we include the borrower's technology similarity with the bank's prior borrowers, and additionally, the borrower market rivalry effect using the Herfindahl-Hirschman Index (HHI) and the borrower credit risk measured by Z-score.

[Insert Table 5 about here]

Table 5 presents the semi-parametric matching results and the point estimation of parameter vector θ. As suggested by Fox (2018) that the p-value is not obtainable in the

[23]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.

[24]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.

[25]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 $X_{b \times f}$.

parameter estimation of such 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 whose technology profiles 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, and borrowers of lower credit risk measured by Altman Z-score with larger 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.[26]

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 determinant in the bank's lending decision-making process.

D A bank learning-by-lending model

Our results so far indicate that banks require lower loan spreads for a borrower who shares a similar technology profile with the banks' prior borrowers. Such effect is likely a result of banks passing on the saved costs of due diligence in evaluating the borrower's technology profile to the borrower and is endogenously determined in bank value maximization. We next turn to an examination of the role of borrower technology similarity in the process of

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

bank learning by lending. Based on the theoretical framework of Farber and Gibbons (1996), Botsch and Vanasco (2019) show that banks learn their borrowers' firm-specific information through repeated lending and such bank learning causally affects loan pricing. We modify their empirical design and include borrower technology value and similarity into the model.

Specifically, consider a risk-neutral bank lending to a borrower of unknown true probability of default π with an information set of I. The bank determines the loan interest rate R and the percentage of loan collateral c to ensure positive expected return:

$$(1 - E[\pi|I])R + E[\pi|I]\, c \geq R_f \tag{8}$$

In other words, the bank charges a loan spread over its funding cost, r, conditional on its estimation of the borrower's default risk and collateral requirement.

$$r = R - R_f \geq \frac{E[\pi|I]}{1 - E[\pi|I]} (R_f - c) \tag{9}$$

We follow Botsch and Vanasco (2019) and parameterize r as a linear function of the expected default probability and loan characteristics w:

$$r \approx \alpha_0 + \alpha_1 E[\pi|I] + \gamma' w \tag{10}$$

The bank's information set I_t of the borrower at time t can be decomposed into $\{z_t,\ S_\tau\}$, where z_t is the firm-specific information observable at time t, and $S_\tau = \{s_1, s_2, \ldots, s_\tau\}$ is the firm information revealed only to the bank after τ loans (i.e., relationship length). We as econometricians observe r, w, and $\tilde{z}$, a subset of z, and can only estimate the following regression model given our dataset:

$$r_{l,f,t} = \alpha_t + \alpha_f + \beta' \tilde{z}_{f,t} + \gamma' w_{l,f,t} + \varepsilon_{l,f,t} \tag{11}$$

where t is the origination time for loan l to borrower firm f. Note that the bank uses full firm characteristics z in estimating $E[\pi|I = \{z, S\}]$, so that the coefficient estimate on $\tilde{z}$ is affected by omitted variables.

The essence of Farber and Gibbons (1996) and Botsch and Vanasco (2019) to detect bank learning is the following. Suppose we can include the unobservable true default probability π in the regression specified by Equation 11, then π would have some positive loading due to the omitted variable bias at relationship time 0, even though the bank has not received any signal s_τ. More importantly, if bank learns firm-specific information over repeated lending and uses the information in loan pricing, we would observe an increasing loading on π in the relationship length τ as the information set S_τ grows.

Empirically, a proxy b_f for π is required such that it is correlated with the unobservable true default probability but is not inside the bank's information set I. However, b_f is likely to be correlated with variables omitted from Equation 11 but observed and used by the bank in pricing the *first* loan, i.e., b_f may be correlated with some $z^* \in (z - \tilde{z})$. To remove this dependency, we orthogonalize b_f on the observable firm characteristics and initial loan terms for the first loan and use the residuals as the proxy variable:

$$b_f^* = b_f - E\left[b_f|\tilde{z}_{f,t_0}, w_{l,f,t_0}, r_{l,f,t_0}\right] \tag{12}$$

Note that we condition on more than observable firm characteristics $\tilde{z}$ and include also the loan spread r_{l,f,t_0} and loan terms w_{l,f,t_0} for the initial loan, which are outcomes of firm characteristics used by the bank in loan pricing but unobserved to us (i.e., the omitted variables). This attempts to ensure that our proxy variable b_f^* is orthogonal to z the firm characteristics observed by bank, and thus leaves only its impact on loan pricing through S the information learned by the bank via repeated lending. Adding b_f^* with a relationship-time-varying coefficient to the previous regression model, we have:

$$r_{l,f,t} = \alpha_t + \alpha_f + \beta'\tilde{z}_{f,t} + \gamma' w_{l,f,t} + \delta_\tau b_f^* + \varepsilon_{l,f,t} \tag{13}$$

As bank learns new information about the borrower over repeated lending, S_τ becomes more important in the bank's estimation of the firm default probability $E\left[\pi_{f,t}|z_{f,t}, s_{f,1}, s_{f,2}, \ldots\right]$. To the extent that b_f^* correlates with S_τ, we expect a growing δ_τ in relationship length.

Botsch and Vanasco (2019) uses two proxies b_f^*, both in the future of the entire sample period to mitigate the concern of them being observable and thus correlated with z. We choose to use the orthogonalized borrower's technology profile five years in the future. We conjecture that, at the first loan origination, the bank is unlikely to knows the borrower's technology profile in five years given the uncertainty about innovation outputs and technology trend. To alleviate the concern that such future technology profile correlates with the bank's information set of the borrower's innovation ability at first loan origination, we also include the borrower's technology profile at the first loan origination in the orthogonalization. Specifically, we consider three different measures five years from the first loan origination, the Kogan et al. (2017) total patent value of the firm (Future Patent Value), the number of patents granted (Future Patent Number), and the total patent citations (Future Patent Citation). Further, to investigate the role of technology similarity in the bank learning process, we include technology similarity and its interactions with the orthogonalized proxy, the relationship length and their interaction term in the model.

[Insert Table 6 about here]

Table 6 presents the results. Panel A shows the first-stage result where we orthogonalize the borrower's future technology profile on the observed firm characteristics, loan characteristics and the borrower's technology profile at the initial loan origination using the sample of all first-time loans. The residuals from the first stage are then used as the orthogonalized proxy in the second-stage regression. Given that our sample period ends in 2020 and we use five-year ahead technology profiles as proxies, loans to borrowers who first borrow after 2015 are removed from the sample. Panel B reports the second-stage triple-interaction result using all loans.

First, we show that the coefficient of the interaction between the orthogonalized proxy and relationship time is negative and significant for all proxies. This implies that the loading on the information proxy is increasing in the relationship time, which suggests banks indeed pick up more firm-specific information from repeated lending, consistent with Botsch and Vanasco (2019). Second, we document an unconditional negative association between technology similarity and loan costs, similar to our baseline results. Moreover, such negative impact of technology similarity on loan costs is larger for borrowers with stronger technology profiles reflected by the orthogonalized proxy. However, we also find positive and significant coefficient estimates for the triple interaction term (Orthogonalized Proxy $\times$ Relationship Time $\times$ Technology Similarity), which indicates that banks tend to hold up such borrowers with high technology similarity (with prior borrowers) and strong technology profiles as their lending relationship strengthens. Alternatively, it indicates a diminishing rate of banks passing on the cost savings due to technology similarity to the borrower as has received more repeated loans. Intuitively, our results highlight an important role of technology similarity in the bank learning-by-lending process. Specifically, banks are willing to offer loans at reduced costs to a new borrower that shares a similar technology profile with the banks' prior borrowers, likely due to the cost savings from conducting less due diligence in evaluating the technology profile of the borrower. As the bank repeatedly lends to the borrower and learns more firm-specific information, such technology similarity is valued less and hence has a smaller impact on loan pricing.

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 borrowers with lower credit risk. 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 7 about here]

Table 7 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 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 measure by Acharya and Mora (2015), the loan-to-deposit shortfall, and its interaction 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 banks of lower liquidity cut more loan spreads for borrowers with similar technology profiles with prior borrowers.

[Insert Table 8 about here]

Table 8 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 Altman's 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 borrowers with relatively low credit risks.[27] 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 borrowing from banks whose prior borrowers they share similar technology profiles with. 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 the technology similarity. This implies that banks cut more loan spreads for borrowers of higher profitability when they have a higher technology similarity with banks' prior borrowers, and further, the documented effect of borrower technology similarity reducing loan spreads concentrates in the more profitable borrowers.

In summary, we show that smaller banks, less-capitalized, or less-liquid banks are more willing to charge lower loan spreads for borrowers with a higher technology similarity with their prior borrowers. The negative effect of borrower technology similarity on loan spreads is mostly clustered in creditworthy or profitable firms, and is stronger for borrowers with lower leverage.

VII Conclusion

In this study, we empirically examine the impact of borrower technology similarity on loan costs. 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 similar technologies. Such effect is robust to controlling for the industry segment similarity between the borrower and prior borrowers which affects bank loan portfolio's industry concentration, and is robust to controlling for

[27] We find similar results using alternative borrower creditworthiness measures such as the borrower distance-to-default and whether the borrower has credit rating.

the intensity of product market competition faced by the borrower. In addition, borrower's technology profile itself 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.

Despite the identification challenges, we show that the 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. Further, using a bank learning model, we show that banks are willing to offer loans at reduced costs to new borrowers sharing similar technologies with prior borrowers initially, but such discount declines as banks learn more borrower firm-specific information through repeated loans. We then find that smaller, less-capitalized or less-liquid banks give larger discounts in loan pricing for borrowers with a higher technology similarity, and moreover it is mostly profitable borrowers with low credit risks and leverages that are granted such discounts.

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Figure 1: **Pairwise Technology Similarity**

Figure 1 illustrates the pairwise technology similarity calculation for a borrower firm i, as at loan origination time t, for the two prior borrowers j and k of the bank in the five years leading to t. The technology similarity is computed based on the patent portfolios of the 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.

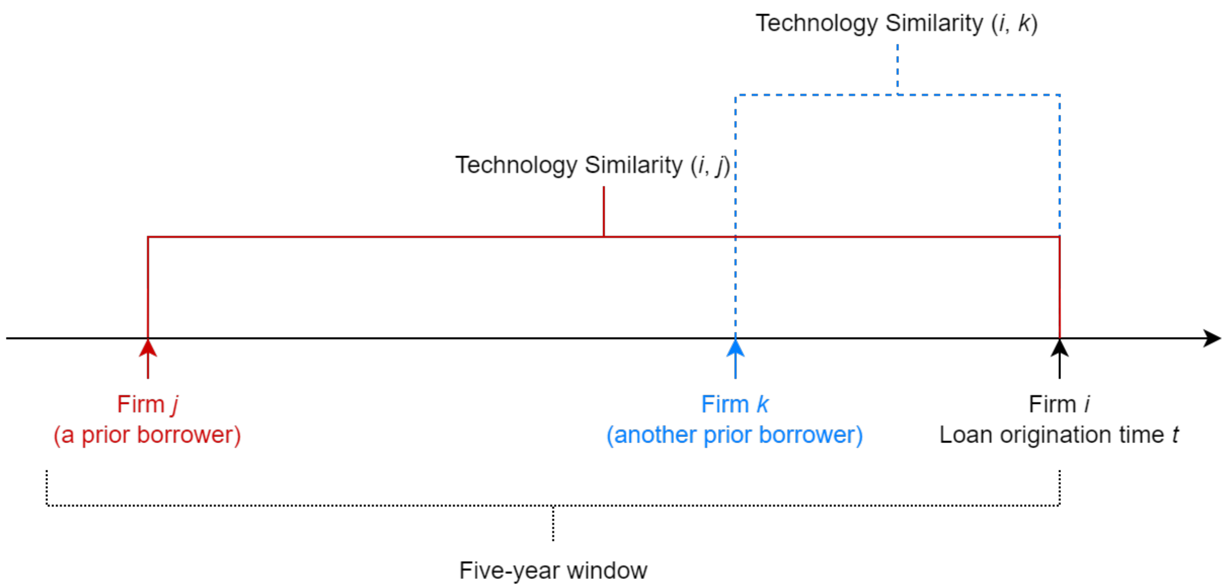

Table 1: **Summary Statistics**

Table 1 presents the summary statistics of our loan sample, which consists of DealScan 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 1^{st} and 99^{th} 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
Borr In Bank Top Ind	36,166	0.190	0.392	0.000	0.000	1.000
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
Total Covenants	36,166	1.395	1.497	0.000	1.000	4.000
Loan Secured	36,166	0.533	0.499	0.000	1.000	1.000
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 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	0.000	1.000	1.000
Borrower Distance-to-Default	28,131	6.439	4.682	1.505	5.219	13.664
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 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 Hoberg and Phillips (2016) three 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 Total Loan Cost**

Table 3 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 Hoberg and Phillips (2016) three product market competition measures, respectively. Columns (5) to (7) additionally control for the borrower's patent stock. 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	-0.433***	-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)
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)
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 4: **Information Content of Technology Similarity**

Table 4 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 in 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	Distance-to-Default	Profitability	Cash Holding
	(1)	(2)	(3)	(4)
Technology Similarity	-0.005***	-10.744***	-0.052***	-0.034***
	(0.002)	(1.155)	(0.011)	(0.011)
Segment Similarity	-0.004**	3.276***	-0.036***	-0.032***
	(0.002)	(1.185)	(0.013)	(0.012)
Absolute difference in size	0.001***	-0.103	0.004***	0.003***
	(0.000)	(0.067)	(0.001)	(0.001)
Absolute difference in leverage	0.018***	0.583	0.068***	0.050***
	(0.001)	(0.547)	(0.006)	(0.005)
Absolute difference in market-to-book ratio	0.005***	0.064	0.135***	0.035***
	(0.002)	(0.992)	(0.015)	(0.012)
Absolute difference in sales growth	0.000***	-0.001	0.000	0.000
	(0.000)	(0.001)	(0.000)	(0.000)
Absolute difference in tangibility	0.002***	1.126**	-0.012**	0.015***
	(0.001)	(0.508)	(0.005)	(0.005)
Absolute difference in patent stock	0.001	1.115	0.031**	0.009
	(0.002)	(1.293)	(0.012)	(0.015)
Absolute difference in patent value	0.000**	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Borrower Industry × Year Fixed Effects	Yes	Yes	Yes	Yes
Lender Fixed Effects	Yes	Yes	Yes	Yes
Observations	36,166	28,041	36,166	36,166
Adjusted R^2	0.243	0.237	0.204	0.130

Table 5: **Semi-Parametric Bank-Borrower Matching**

Table 5 shows the result of the semi-parametric 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]
Borr.Bank-Dep. × Bank Cap.	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 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]
Borr.in Bank's Top Inds.	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 6: **Borrower Technology Similarity in Bank Learning**

Table 6 reports the results of Farber and Gibbons (1996) and Botsch and Vanasco (2019) two-stage learning regression. Specifically, Panel A shows the first-stage results where we orthogonalize the borrower's future technology proxies (five years from the first loan) on borrower and loan characteristics observed at bank-borrower relationship time 0. Panel B reports the second-stage results where we regress the natural logarithm of loan spread on orthogonalized firm technology proxy, technology similarity, relationship time and their interactions. Note that the sample size declines due to removed loans if the first loan (from a bank) is after 2015. 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.

Panel A: First stage (relationship time 0)

Dependent Variable:	Future Patent Value (1)	Future Patent Number (2)	Future Patent Citation (3)
ln(Loan Spread)	-0.068***	-0.093***	-0.066***
	(0.019)	(0.023)	(0.017)
Borrower Size	0.106***	0.081***	0.063***
	(0.013)	(0.013)	(0.009)
Borrower Leverage	-0.050	-0.034	-0.061
	(0.046)	(0.060)	(0.044)
Borrower Z-score	-0.405	0.785	0.759
	(0.780)	(1.030)	(0.812)
Borrower Profitability	0.353***	0.346**	0.249**
	(0.105)	(0.149)	(0.121)
Borrower Market-to-Book	0.195	0.383	0.140
	(0.194)	(0.281)	(0.157)
Borrower Cash	0.010	0.093	0.171*
	(0.081)	(0.122)	(0.098)
Borrower Has Credit Rating	0.026	0.035	0.021
	(0.030)	(0.031)	(0.023)
ln(Loan Size)	-0.031***	-0.023**	-0.008
	(0.009)	(0.011)	(0.007)
ln(Loan Maturity)	-0.020	-0.025	-0.006
	(0.014)	(0.017)	(0.013)
Loan Secured	-0.009	-0.002	-0.001
	(0.020)	(0.025)	(0.020)
Proxy at time 0	0.110***	0.464***	0.160***
	(0.008)	(0.029)	(0.012)
Borrower Industry × Year Fixed Effects	Yes	Yes	Yes
Lender Fixed Effects	Yes	Yes	Yes
Loan Type and Purpose Fixed Effects	Yes	Yes	Yes
Observations	14,394	14,394	14,394
Adjusted R^2	0.341	0.454	0.282

Table 6: **Continued**

Panel B: Second Stage (all loans)

Orthogonalized Proxy:	Patent Value	Patent Number	Patent Citation
	(1)	(2)	(3)
Orthogonalized Proxy	0.041**	0.036***	0.020*
	(0.016)	(0.011)	(0.012)
Relationship Time	0.001	0.002	0.002
	(0.002)	(0.002)	(0.003)
Orthogonalized Proxy × Relationship Time	-0.014***	-0.009***	-0.007*
	(0.004)	(0.003)	(0.004)
Technology Similarity	-0.499***	-0.490***	-0.463***
	(0.107)	(0.108)	(0.108)
Orthogonalized Proxy × Technology Similarity	-0.658***	-0.559***	-0.508***
	(0.168)	(0.114)	(0.132)
Relationship Time × Technology Similarity	0.042*	0.032	0.034
	(0.025)	(0.026)	(0.026)
Orthogonalized Proxy × Relationship Time × Technology Similarity	0.112***	0.085***	0.071**
	(0.033)	(0.020)	(0.030)
Segment Similarity	0.156	0.159	0.155
	(0.098)	(0.098)	(0.098)
Borrower Size	-0.076***	-0.077***	-0.078***
	(0.006)	(0.005)	(0.005)
Borrower Leverage	0.568***	0.570***	0.571***
	(0.027)	(0.027)	(0.027)
Borrower Z-score	-2.110***	-2.076***	-2.108***
	(0.456)	(0.455)	(0.457)
Borrower Profitability	-1.089***	-1.086***	-1.089***
	(0.065)	(0.065)	(0.065)
Borrower Market-to-Book	-0.302***	-0.308***	-0.306***
	(0.076)	(0.076)	(0.076)
Borrower Cash	0.086*	0.089*	0.087*
	(0.050)	(0.051)	(0.051)
ln(Loan Size)	-0.098***	-0.098***	-0.098***
	(0.005)	(0.005)	(0.005)
ln(Loan Maturity)	0.020***	0.021***	0.021***
	(0.008)	(0.008)	(0.008)
Loan Secured	0.389***	0.389***	0.389***
	(0.010)	(0.010)	(0.010)
Borrower Industry × Year Fixed Effects	Yes	Yes	Yes
Lender Fixed Effects	Yes	Yes	Yes
Loan Type and Purpose Fixed Effects	Yes	Yes	Yes
Observations	32,919	32,919	32,919
Adjusted R^2	0.653	0.653	0.653

Table 7: **Heterogeneous Effects of Borrower Technology Similarity: Banks**

Table 7 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 8: **Heterogeneous Effects of Borrower Technology Similarity: Borrowers**

Table 8 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	-0.541***	0.191
	(0.129)	(0.158)	(0.158)
Technology Similarity × Borrower Z-score	-18.223***		
	(6.069)		
Technology Similarity × Borrower Leverage		0.865**	
		(0.415)	
Technology Similarity × Borrower Profitability			-4.527***
			(0.991)
Borrower Z-score	-8.557***		
	(0.433)		
Borrower Leverage		0.576***	
		(0.028)	
Borrower Profitability			-1.114***
			(0.058)
Segment Similarity	0.246***	0.285***	0.274***
	(0.095)	(0.095)	(0.095)
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	-0.074***	-0.072***	-0.079***
	(0.006)	(0.005)	(0.006)
Borrower Market-to-Book	-0.435***	-0.490***	-0.332***
	(0.074)	(0.082)	(0.073)
Borrower Cash	-0.145***	0.071	-0.229***
	(0.048)	(0.051)	(0.048)
Borrower Has Credit Rating	0.058***	0.032***	0.081***
	(0.012)	(0.012)	(0.012)
ln(Loan Size)	-0.100***	-0.109***	-0.096***
	(0.005)	(0.004)	(0.005)
ln(Loan Maturity)	0.011	0.001	0.015**
	(0.007)	(0.007)	(0.007)
Loan Secured	0.423***	0.420***	0.426***
	(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

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' prior lending portfolios in 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
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
Borrower Distance to Default	Bharath and Shumway (2008) naive distance-to-default measure	Compustat

Table A1: **Continued**

Variable	Definition	Source
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 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: **Difference-in-Differences Regression**

Table A2 reports the difference-in-differences regressions using TRIPS as the exogenous shock. Specifically, we employ the exact same control variables as the baseline model (Equation 3 and column (1) in Table 2), except for column (1) which alleviates the concern of bad controls. We keep the borrower industry fixed effects, lender fixed effects, loan type fixed effects and loan purpose fixed effects. We treat borrowers with technology similarity greater than the median technology similarity each year as the treated group and the years after 1995 as the post-TRIPS period. For simplicity, we do not report the coefficient estimates of the loan-level and borrower-level controls. 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)
Treated	-0.281***	-0.048	-0.050*	-0.037	-0.045
	(0.041)	(0.029)	(0.030)	(0.029)	(0.029)
Post	-0.129***	-0.060***	-0.059***	-0.062***	-0.061***
	(0.028)	(0.023)	(0.023)	(0.023)	(0.023)
Post × Treated	-0.398***	-0.113***	-0.113***	-0.106***	-0.094***
	(0.038)	(0.029)	(0.029)	(0.029)	(0.029)
Segment Similarity			0.106		
			(0.196)		
Borrower Product Market HHI				-0.180***	
				(0.034)	
Borrower Patent Value					-0.003***
					(0.001)
Prior Relationship		0.003	0.001	-0.001	0.002
		(0.019)	(0.019)	(0.019)	(0.019)
Loan Level Controls	No	Yes	Yes	Yes	Yes
Borrower Level Controls	No	Yes	Yes	Yes	Yes
Loan Type and Purpose Fixed Effects	Yes	Yes	Yes	Yes	Yes
Borrower Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Lender Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	8,411	8,411	8,411	8,411	8,411
Adjusted R^2	0.392	0.644	0.643	0.646	0.646

Table A3: **Robustness Check: Borrower Technology Similarity of Different Windows and Loan Spread**

Table A3 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 also construct the segment similarity using banks' past 1-year, 3-year, 7-year and all history lending portfolios. The window type of segment similarity is consistent with that of borrower technology similarity across all regressions. 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 Window	
	(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