Bank Geographic Diversification and Corporate Innovation: Evidence from Lending Channel

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Abstract

We examine the causal relationship between bank geographic diversification and corporate innovation in borrowing firms. Following Goetz, Laeven, and Levine (2013, 2016), we integrate the staggered interstate bank deregulation into a gravity model to construct a time-varying and bank-specific instrument for geographic diversification, which enables us to disentangle the effect of bank deregulation on geographic expansion from that on bank competition. We find that bank geographic diversification boosts borrowing firms’ R&D investments, and innovation output (patent and citation counts). In addition, bank geographic diversification enables firms to expand innovation scope beyond their core business, and explore innovation in new areas, all of which enhance the value of innovation. We further document that diversified banks offer loan contracts with fewer and less stringent covenants, and bank credit alleviates borrowers’ financial constraints, implying that debt covenant and credit supply are two channels by which bank geographic diversification spurs corporate innovation.

JEL Classification: G32; G39; G21; G28

Key Words: Bank geographic diversification; gravity model; innovation; bank deregulation; debt covenant; financial constraint
I. Introduction

A stream of recent literature documents that bank deregulation impacts corporate innovation and thereby economic growth (e.g., Chava, Oettl, Subramanian, and Subramanian 2013; Amore, Schneider, and Žaldokas 2013; Cornaggia, Tian, and Wolfe 2015; Hombert and Matray 2016). Prior studies typically employ either an interstate deregulation dummy (e.g., Kerr and Nanda 2009; Amore, Schneider, and Žaldokas 2013; Chava et al. 2013), or a state-level branching restriction index (i.e., Rice and Strahan 2010; Cornaggia, Tian, and Wolfe 2015; Hombert and Matray 2016) to proxy for the extent of state level deregulation or bank competition, while ignoring potential different exposures to the deregulation shocks among individual banks within the same state. However bank deregulation influences both bank geographic expansion and bank competition, using state level deregulation proxy prevents one from disentangling the effect of bank geographic expansion versus bank competition. Moreover, Amore, Schneider, and Žaldokas (2013) find that following bank deregulation the increase in credit supply spurs firm innovation; yet they acknowledge that “we do not establish whether the increase in innovation stems directly from bank lending to innovative firms.” This is because bank deregulation might have fostered the development of non-bank financial institutions such as venture capital and private equity firms, which in turn provide funding for innovation projects.\(^1\)

In this paper we connect banks with firms through bank loan contracts and investigate the causal effect of bank geographic diversification on the innovation activities of borrowing firms, using a gravity-deregulation approach (explained below). Such an approach enables us to disentangle the impact of bank deregulation on bank geographic expansion and bank competition,

\(^1\) Amore, Schneider, and Žaldokas (2013, P837) state “Although we do not establish whether the increase in innovation stems directly from bank lending to innovative firms, our results reinforce the notion that changes in the supply of credit have strong effects on corporate policies.”
and pin down whether increase in innovation is directly attributable to geographically diversified banks’ lending to innovative firms.²

Empirical research investigating how bank geographic diversification affects corporate innovation is subject to an endogeneity problem, i.e., omitted variables might affect both bank geographic expansion and corporate innovation. For example, firms in more innovative regions tend to be more innovative due to knowledge spillover and learning effect. In the meantime, banks may be attracted to more innovative regions because of the business opportunities so they tend to set up new branches and subsidiaries there. To overcome this empirical challenge, we follow Goetz, Laeven, and Levine (2013, 2016) and use the staggered interstate bank deregulation as an exogenous shock to bank geographic expansion, then we integrate the deregulation into a gravity model that uses pre-determined variables such as distance and relative market size to project bank geographic expansion in foreign states. Using the projected share of foreign state operation, we construct an exogenous time-varying BHC-specific instrument of geographic diversification with which we can tease out a causal relationship between bank diversification and borrowing firms’ innovation.³

We next use the Dealscan database to link each borrowing firm with its lenders via bank loan contracts. By doing so we are able to directly examine how a bank’s geographic diversification resulted from interstate deregulation affects the innovation activities of its borrowing firms. Such a direct link enables us to pin down whether the increase in innovation is

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² Amore, Schneider, and Žaldokas (2013) propose that bank geographic diversification is a channel to explain the impact of bank deregulation and find that the impact of bank deregulation on innovation is more pronounced in states with more geographically diversified banks. However, they do not directly test the relationship between bank geographic diversification and firm innovation.

³ Throughout of the paper we use bank and bank holding company (BHC) interchangeably.
directly attributable to geographically diversified banks’ lending to their borrowers rather than due to increased bank competition or enhanced development of non-bank financial institutions.

We perceive that bank geographic diversification can spur corporate innovation for the following two reasons. First, bank interstate deregulation allows a bank to acquire other banks and/or open de novo branches across state borders, promoting bank expansion geographically.4 As a result, bank credit supply increases in the lending market, which may drive down the cost of borrowing and enable borrowers to undertake more innovative and risky projects, hence stimulating corporate innovation. Supporting this argument, Rice and Strahan (2010), and Benfratello, Schiantarelli, and Sembenelli (2008) document that bank deregulation lowers the cost of bank loans and relaxed financial constraints of small firms.

Second, to the extent that bank geographic diversification reduces idiosyncratic risk as shown in Goetz, Laeven, and Levine (2016), more geographically diversified banks may be willing to take greater risk, i.e., lending to firms that take riskier and more innovative projects (Amore, Schneider, and Žaldokas 2013). Prior literature documents that debt contract terms are crafted conditional on lenders’ financial condition. For example, Murfin (2012) finds that banks experienced recent loan defaults write tighter debt contracts to subsequent borrowers than their peers do. As recent defaults update the lender's perception about its own poor screening ability, banks may impose tighter loan covenants to compensate for the weaker ex ante screening. Diversified banks might be willing to lend on more favorable loan contract terms (i.e., fewer covenants and/or less stringent covenants) to borrowing firms as they are more geographically diversified so less concerned of risk. Fewer and less stringent covenants reduce the likelihood of

4 In her address to the California League of Savings Institutions in San Diego in April 1986, Federal Reserve Board Governor Martha Seger commented “interstate expansion allows for the diversification of sources and uses of funds. Dependence on economic conditions in a very limited number of local markets can be reduced by a wider range of operations”.
lenders’ intervention over the real and financial decisions of the borrowing firms, stimulating innovation activities. In addition, Atanassov (2016) argues that firms with less stringent covenants have more flexibility and tolerance to experiment with innovative activities. In sum, diversified banks are more tolerant for innovation in borrowing firms and write less stringent loan contracts that are conducive to corporate innovation.

We employ various measures to capture firms’ innovation activities. We use R&D expenses and R&D stock as measures of innovation input. To measure innovation output, we follow existing studies and employ patent-based metrics including number of patents and number of citations per patent to proxy for the quantity and quality of innovation, respectively (e.g., Chava et al. 2013; Amore, Schneider, and Žaldokas 2013; Cornaggia, Tian, and Wolfe 2015; Sunder, Sunder, and Zhang 2017). Furthermore, we examine firms’ innovation scope – percentage of patents related or unrelated to firms’ core business to shed light on the focus of innovation projects. We also probe innovation search strategy in unknown areas to provide more insights on firms’ innovation profile. Finally, following Kogan, Papanikolaou, Seru, and Stoffman (2017), we assess the economic value associated with firm innovation which is proxied by equity market abnormal return in response to the announcement of patent grants.

Empirical results reveal a positive causal relationship between bank geographic diversification and corporate innovation, including innovation input measured by R&D stock and R&D expenses, and innovation output proxied by both patent and citation counts. The results are consistent with Amore, Schneider, and Žaldokas (2013) in that credit supply stimulate firms’ innovative activities. Going beyond Amore, Schneider, and Žaldokas (2013), we establish the direct link between bank lending via geographic expansion and corporate innovation in borrowing firms by connecting each firm with its lenders using bank loans data in Dealscan. Second, we find that
bank geographic diversification allows borrowing firms to expand innovation scope by investing more in projects that are unrelated to their core business, and extend their innovation search strategy in unknown areas. Lastly, we document that bank geographic diversification leads to significantly higher economic values of patents in borrowing firms.

The aforesaid theoretical arguments suggest that bank geographic diversification may spur corporate innovation by increasing bank credit supply and/or providing more lenient bank loan terms such as fewer covenants and less restrictive covenants. We next explore how debt covenant and credit supply act as channels by which bank geographic diversification impacts innovation in borrowing firms. As bank geographic diversification reduces risk (Goetz, Laeven, and Levine 2016), diversified banks may be willing to lend on less restrictive contract terms, which reduces lenders’ interference over the investment and financing decisions of borrowing firms. This in turn stimulates innovation. In addition, firms with less stringent covenants have more financial flexibility and are more tolerant to experimenting innovative ideas (Atanassov 2016). To the extent that bank geographic expansion increases bank credit supply, which helps to alleviate borrowing firms’ financial constraints and in turn promote their innovation activities, we expect that bank geographic diversification alleviates borrowers’ financial constraints. We find that bank geographic diversification leads to lower financial constraints proxied by \( WWIndex \), confirming our conjecture.

We find that geographically diversified banks tend to lend on more pardoning terms, including fewer number of financial and general covenants, fewer capital covenants, and less stringent covenants in their debt contracts, supporting the debt covenant channel. We also find that bank geographic diversification leads to lower financial constraints proxied by \( WWIndex \). This result lends support to the credit supply channel – bank geographic expansion increases bank credit
supply, which helps to alleviate borrowing firms’ financial constraints and in turn promote their innovation activities.

There are four recent studies examining the impact of bank deregulation on corporate innovation. More specifically, Amore, Schneider, and Žaldokas (2013) document that interstate bank deregulation enhances both quantity and quality of innovation by public manufacturing firms. Cornaggia, Tian, and Wolfe (2015) focus on interstate branching deregulation and find that deregulation reduces state-level innovation by public firms. However, innovation by private firms increases as bank competition enables small and innovative firms to obtain bank loan financing so that they remain independent rather than being acquired by large public firms. Chava et al. (2013) find that intrastate (interstate) branching deregulation leads to a reduction (an increase) in the level and risk of innovation by young and private firms. Hombert and Matray (2016) focus on intrastate branching deregulation and find that innovation by small firms declines following intrastate deregulation as bank competition sever lending relationship, whereas innovation by large firms does not decline.

Our paper differs from the four aforesaid studies in several ways. First, the four studies all examine how state-level bank deregulation affects innovation activities in all firms located in each state from the perspective of increased credit supply or bank competition. As Amore, Schneider, and Žaldokas (2013) acknowledge that “we do not establish whether the increase in innovation stems directly from bank lending to innovative firms,” bank deregulation might have enhanced bank geographic expansion, increased bank competition, and fostered the development of non-bank financial institutions such as venture capital and private equity firms, all of which might have affected corporate innovation. In our study, we link banks with firms through bank loan contracts.
and investigate a direct causal effect of the extent of banks’ geographic diversification on the innovation activities of their borrowers.

Second, bank deregulation leads to an increase in both bank geographic expansion and bank competition, yet the state-level deregulation dummy or branching restriction index used in prior studies does not permit researchers to differentiate these two effects. Our paper is the first to disentangle the effect of interstate bank deregulation on geographic expansion versus bank competition, hence establishing a direct link between bank lending via geographic expansion and corporate innovation in borrowing firm. Consequently our study directly sheds light on the causal effect of banks’ geographic diversification on their borrowers’ innovation activities through the lending channel, without potential confounding effects from bank competition or development of non-bank financial institutions that might be associated with the bank deregulation events.

Our paper contributes to the existing literature in the following ways. First, employing a gravity-deregulation approach per Goetz, Laeven, and Levine (2013, 2016), we are able to construct a bank-specific and time-varying instrumental variable for bank geographic diversification. The exogenous variation of instrument arises from the interstate bank deregulation shock, pre-determined geographic distance between a BHC headquarters and a foreign state, and relative market size of home state vs. foreign state. This approach allows us to disentangle the effect of interstate bank deregulation on geographic expansion versus bank competition, and examine the causal relationship between bank geographic diversification and corporate innovation.

Second, we fill the void in corporate innovation literature by investigating how lender characteristics (i.e., bank geographic diversification) might affect corporate innovation in borrowing firms. While the existing literature has a good understanding about the effects of various
market factors and firm-specific characteristics on innovation, studies examining how banks affect innovation are relatively sparse. An exception is Gu, Mao, and Tian (2017), who investigate the effect of bank interventions on corporate innovation and firm value via the lens of debt covenant violations. We argue that lenders may affect corporate innovation outside of covenant violations, through supplying bank credit and altering the strictness of debt contract terms. Our study sheds light on how bank diversification creates externality on its borrowing firms’ investment behavior in innovation. Such insights are of great interests for both corporations and financial market regulators.

Third, we identify a novel channel via which banks affect firm innovation – the debt covenant channel. The use of covenants in debt contracts is motivated by their ability to mitigate incentive conflicts between managers and creditors (Smith and Warner 1979). Nevertheless prior research has documented that tight loan contracts significantly restrict the corporate behavior and financial and operational flexibility (Bradley and Roberts, 2003; Dichev and Skinner, 2002; Chava and Roberts, 2008). Our paper demonstrates that providing more lenient covenants by geographically diversified banks permits financial and operational flexibility in borrowing forms, hence spurring firm innovation. In that sense, our paper complements the literature in how restrictive debt covenants affect firm’s operational flexibility, especially in long term investments in innovative projects.

Fourth, we contribute to the literature by documenting the impact of bank geographic diversification not only on the quantity and quality of innovation, but also on the scope of the

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5 Existing studies on the determinants of corporate innovation focus on either market factors such as competition, bankruptcy laws, labor laws, corporate venture capital, and investors’ tolerance for failure (Aghion, Bloom, Blundell, Griffith, and Howitt 2005; Acharya and Subramanian 2009; Acharya, Baghai, and Subramanian 2013 and 2014; Chemmanur, Loutskina, and Tian 2014; Tian and Wang 2014), or firm-specific characteristics including CEO overconfidence, stock return liquidity, analyst coverage, and institutional ownership (Galasso and Simco 2011; Fang, Tian, and Tice, 2014; He and Tian, 2013; Aghion, Van Reenen, and Zingales 2013).
innovation portfolios, the search strategy of firms’ innovation in unknown areas, and economic value of innovation. Such analyses portray a richer picture on the effect of bank geographic diversification on firm innovation.

The rest of the paper proceeds as follows: Section II introduces data and methodology; Section III presents models; Section IV discusses empirical results, channel effects, and robustness checks; Section V concludes.

**II. Data and Methodology**

**2.1 Sample Selection**

We obtain data from various sources. Bank data are from Bank Holding Companies (BHC) database and FDIC’s Summary of Deposits (SOD). BHC database provides BHC-specific information. The SOD database provides data on deposits at branch and subsidiary level for each BHC. Data on stock prices, returns, and market capitalization are from the Center for Research in Security Prices (CRSP) database. We obtain detailed data on patents from NBER U.S. Patent Citations Database. DealScan database compiled by the Loan Pricing Corporation (LPC) of Thomson Reuters provides detailed bank loan contract information such as lenders, loan amount, loan spread, maturity, collateral, and covenants, etc.

We describe detailed steps on how we construct the sample for our analysis in Appendix A. Our final sample contains 40,065 firm-bank-year observations with 3,449 firms borrowing from 153 BHCs over the sample period of 1986 to 2006. We start the sample period from 1986Q3 when the BHC database began coverage, and end it in 2006 to avoid any confounding effect of the recent 2007–2009 financial crisis. We winsorize all continuous variables at the top and bottom 5% to remove outliers.6

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6 We obtain similar results as we winsorize all continuous variables at the top and bottom 1%.
2.2 Variable Construction

2.2.1 Bank Geographic Diversification

Bank geographic diversification is proxied by the dispersion of a bank’s deposits across states, which is one minus the Herfindahl-Hirschman index (HHI) that is computed as one minus the sum of the squared ratios of the total deposits from all branches in each state to the sum of the total deposits in all of the states where a BHC operates, \((1-\text{HHI})\). This index is between zero and one, with larger values indicating a higher degree of geographic diversification.

2.2.2 Innovation Measures

2.2.2.1 Innovation input

To proxy for innovation input, we follow Chava, Nanda, and Xiao (2015) and compute R&D (R&D expense scaled by total assets) and R&D Stock, the latter is obtained by depreciating a firm's R&D expenses over 5 years at a depreciation rate of 20%, as shown below:

\[
R&D_{Stock_{i,t}} = R&D_{i,t} + 0.8R&D_{i,t-1} + 0.6R&D_{i,t-2} + 0.4R&D_{i,t-3} + 0.2R&D_{i,t-4} \tag{1}
\]

Following existing studies (e.g., Mao and Zhang 2016; Sunder, Sunder, and Zhang 2017), we set missing values in R&D expenses to zero.

2.2.2.2 Innovation output

We use patent-based metrics including patent counts and citation counts to proxy for firm innovation output following the existing studies (e.g., Chava et al. 2013; Amore, Schneider, and Žaldokas 2013; Cornaggia, Tian, and Wolfe 2015; Acharya and Xu 2017; among others). Specifically, we obtain patent data from NBER U.S. Patent and Citations database over 1976-2006. To measure innovation quantity, we use the total number of patents filed (and eventually granted) in a given year. We use patent application year instead of grant year to better capture the timing of
innovation activities, as there could be two to three years of lag between patent application and grant year (Hall, Jaffe, and Trajtenberg 2001).

To measure innovation quality, we use the number of non-self-citations each patent receives in the subsequent years. We follow Hall, Jaffe, and Trajtenberg (2001, 2005), Fang, Tian, and Tice (2014), and Mao and Zhang (2016) to address the truncation issue associated with patent and citation counts. More specifically, we compute adjusted patent counts by dividing the number of patents a firm has by the cumulative application-grant lag distribution. Adjusted citation counts is obtained by dividing the number of non-self-citations each patent receives by the fraction of predicted lifetime citations. To account for the right skewness of patent data, we take a natural logarithm of one plus the patent counts ($\ln(1+\text{Pat})$) and the natural logarithm of one plus citation counts ($\ln(1+\text{Cite})$) as the main measures of innovation output.

2.2.2.3 Innovation scope

In addition, we explore firm’s innovation scope. The U.S. Patent and Trademark Office (USPTO) assigns each patent a three-digit technology class, which can be mapped to one or multiple two-digit SIC codes based on the concordance table developed by Hsu, Tian, and Xu (2014). If the patents are in a firm’s main two-digit SIC industry we classify them as related patents, otherwise as unrelated patents. We compute the number of related patents for each firm by multiplying the number of patents with the corresponding mapping weights ($\text{Related}$), which measures the number of patents related to a firm’s core business. We calculate the number of unrelated patents by subtracting the total number of patents a firm has in a given year by the number of related patents ($\text{Unrelated}$), which measures the number of patents unrelated to a firm’s core business.

2.2.2.4 Innovation search strategy in unknown areas
To further explore the innovation search strategy, we follow Balsmeier, Fleming, and Manso (2017) and construct two measures of innovation search strategy in unknown areas. The first measure *Unknown* is proxied by the natural logarithm of one plus the number of patents filed in technology classes that are previously unknown to the firm. The second measure *Techproximity* is a continuous variable measuring the technological proximity between the patents filed in the current year and the existing patent portfolio held by the same firm up to the previous year.

2.2.2.5 Economic value of patents

To investigate the value implications of our findings, we examine the economic value of innovation that is based on stock market reactions to announcements of patent grants (Kogan et al. 2017). The advantage of using stock market reactions to capture patent value is that asset prices are forward-looking and hence provide us with an estimate of the private value to the patent holder that is based on ex-ante information. Since many firms hold more than one patent, we compute the average of value of these patents (*Patent_value_avg*) and the sum of the value of all patents (*Patent_value_sum*).

2.2.3 Control Variables

Following Fang, Tian, and Tice (2014) and Mao and Zhang (2016), we include a set of firm-specific characteristics as control variables to explain firm innovation, including firm size, asset tangibility, capital expenditure, profitability, leverage, growth opportunity, product market competition, financial constraints, and firm age. Firm size is proxied by the logarithm of total sales (*Ln(sales)*). Asset tangibility is proxied by net property, plants and equipments scaled by total assets (*PPE*). Capital expenditure is measured by capital expenditures divided by total assets.

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7 The market value of new patent grants is computed by Kogan et al. (2017) and available at https://iu.box.com/patents.
Profitability is measured by return on assets (ROA). Leverage is proxied by total debt divided by total assets (Leverage). Growth opportunity is measured by Tobin’s Q, which is the book value of total assets plus market value of total equity minus book value of total equity, then divided by book value of total assets (Tobin Q). Product market competition is measured by the Herfindahl index based on segment annual sales using 2-digit SIC codes (H-index). To account for the nonlinear effect of product market competition, we also include the squared term of H-index (H-index^2). Financial constraint is measured by KZIndex as defined in Kaplan and Zingales (1997). Firm age is measured as the logarithm of number of years a firm is listed in Compustat (Ln(age)), with the inception year being the first year when a firm initially appears in COMPUSTAT. Detailed variable definitions are summarized in Appendix B.

2.3 Descriptive Statistics

Panel A of Table 1 presents the summary statistics of the innovation variables and other firm-specific characteristics of our final sample. An average sample firm has 17.00 patents, with each patent on average receiving 4.73 citations. Among the patents a firm receives, 2.15 (4.92) patents are related (unrelated) to its core business. An average firm have 0.719 patent in unknown technology areas. An average firm invests $43.02 million in R&D expenses, average R&D stock is $120.60 million. Average economic value per patent is $3.03 million, and average total economic value for all patents for a firm in a year is $71.13 million.

Panel B of Table 1 provides the summary statistics of bank-specific variables. An average sample bank operates 354 branches in 4.66 states. The average degree of geographic diversification for a sample bank is 0.312.

--- Insert Table 1 here ---
III. Identification Strategy and Models

3.1 Identification strategy

Before 1978, U.S. banks were largely prohibited from out-of-state banking. In 1978 Maine became the first state that relaxed interstate banking restriction. Alaska and New York followed suit in 1982. Over the next decade or so, states either unilaterally opened state borders to allow the entry of out-of-state banks, or signed reciprocal bilateral and multilateral agreements with other states allowing interstate banking at different time and various pace (Amel 1993). The wave of interstate bank deregulation culminated in the passage of Riegle-Neal Interstate Banking and Branching Efficiency Act (IBBEA) in 1994, which allows nationwide acquisition of banks and opening de novo branches across state borders, and thereby making nation-wide interstate banking a reality.

In the evolution of interstate bank deregulation, states removed restrictions on interstate banking in different years and in a staggered manner over time, which generates exogenous shocks to bank geographic expansion. In this study, we follow Goetz, Laeven, and Levine (2013, 2016) and integrate the staggered interstate bank deregulation into a gravity model that uses pre-determined variables such as distance and relative market size to project bank geographic expansion in foreign states, based on which we construct an exogenous time-varying BHC-specific instrument of geographic diversification which allows us to tease out a causal relationship between bank diversification and borrowing firms’ innovation. The instrument variable for bank geographic diversification arises from three plausibly exogeneous sources of variation including the exogenous interstate bank deregulation shock, pre-determined geographic characteristics including distance between bank headquarters and foreign state, and relative market size between home and foreign state.
We summarize how we carry out this task as follows: First, we exploit the staggered interstate bank deregulation from 1970s to mid-1990s based on Amel (1993), and construct each state-pair in a year on whether a BHC headquartered in one state can legally enter a foreign state. We determine the actual date that Riegle-Neal Act of 1994 becomes effective in each state based on Rice and Strahan (2010). Consistent with prior studies on bank branching deregulation (i.e., Jayaratne and Strahan 1996), we focus on BHCs headquartered in the 48 contiguous states and the District of Columbia. We further exclude the state of Delaware and South Dakota to avoid any confounding effect.8

Second, we integrate this state- and time-varying interstate bank deregulation into a gravity model that uses distance, relative market size and common border between two states to project BHC deposit expansion across state borders, based on which we construct a BHC-specific and state- and time-varying instrumental variable of geographic diversification. In the next section, we detail the gravity-deregulation model based on which we compute the instrument and how we use it in a two-stage least squares framework to investigate the causal effect of bank geographic diversification on innovation in borrowing firms.

3.2 The Gravity-Deregulation Model

In economics literature a gravity model is used to construct instrumental variable of bilateral trade volume between countries in order to assess the causal relationship between international trade volume and outcome variables such as income (Frankel and Romer 1999; Helpman, Melitz, and Rubinstein 2008). Geographic characteristics such as market size and geographic distance between countries are highly correlated to bilateral trade volume between two countries, yet do not influence

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8 Shortly before removing bank branching restrictions, South Dakota and Delaware removed usury ceilings on credit card loans and other types of consumer loans in 1980 and 1981 respectively. Therefore we preclude both states to avoid any confounding effects.
income, and hence are valid instruments for international trade across countries. Building on this idea, Goetz, Laeven, and Levine (2013, 2016), and Levine, Lin and Xie (2016) are among the first in finance literature to integrate interstate bank deregulation into a gravity model that employs geographic distance and relative market size to project banks’ geographic expansion in foreign states.

Frankel and Romer (1999) find that common border shared by two countries also plays an important role in determining bilateral trade volume. Therefore, we include a common border dummy to account for the possibility that a BHC is more likely to expand to a foreign state that shares a common border with its home state. We also replace state population used in Goetz, Laeven, and Levine (2013, 2016) with state Gross State Product (GSP) which more accurately reflects the size of the market and the economy of each state. We include the ratio of GSP in home state to that in foreign state.9

Our sample used for the gravity model includes all possible pairs of BHCs (b) and states (j) over the period of 1986Q3-2006Q4. Given that the percentage of deposits a BHC (b) has in a particular state j (Share) is bound between zero and one, and many observations have zero values as BHCs are not legally permitted to enter in many foreign states, OLS regression will result in biased estimates. Therefore we follow Papke and Wooldridge (1996, 2008) and employ a fractional logit model to estimate the following model:

$$\text{Share}_{b,ijt} = \beta_1 \text{Distance}_{bij} + \beta_2 \ln(\text{GSP}_{it}/\text{GSP}_{jt}) + \beta_3 \text{CommonBorder}_{ij} + \beta_4 \text{HomeState}_i + \epsilon_{bijt},$$

(2)

where the dependent variable $\text{Share}_{b,ijt}$ is the percentage of BHC b’s deposits in all subsidiaries in state j in year t and BHC b is headquartered in state i. $\text{Distance}_{bij}$ is the straight-line distance

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9 Our results remain qualitatively the same as we use the exact same gravity-deregulation model in Goetz, Laeven, and Levine (2013, 2016).
between BHC b’s headquarter location in state i and the capital of state j. \( \ln(\text{GSP}_{it}/\text{GSP}_{jt}) \) is the natural logarithm of the ratio of Gross State Product (GSP) of BHC b’s home state i to that of a foreign state j in year t. \( \text{CommonBorder}_j \) is an indicator that equals to one if state i and state j share a common land border. \( \text{HomeState}_i \) is a dummy variable that equals one for all BHC-state pairs where BHC b receives deposit in its home state i (i.e., when \( i=j \)). We include the \( \text{HomeState}_i \) dummy to capture potential difference in diversification within home states versus across state borders.

Banks are more likely to diversify into a geographically proximate state because the cost of doing so is lower, thus we expect a negative coefficient estimate of \( \beta_1 \). Since BHCs in general are more likely to expand to larger markets than smaller ones, thus we expect a negative coefficient estimate of \( \beta_2 \). If two states share a common land border, banks are more likely to enter to each other’s territory due to a lower cost of expansion, suggesting a positive sign of \( \beta_3 \). Finally, BHCs are more likely to expand business within its home state, therefore we predict \( \beta_4 \) to be positive.

Results are presented in Table 2. Average marginal effects are reported and standard errors are clustered at state-year level. As expected, the coefficient estimate on geographic distance between the BHC’s headquarter and a foreign state capital is negative, indicating BHCs are more likely to expand to geographically proximate state. The coefficient estimate on relative market size is negative and significant, suggesting that BHCs located in a state with larger market are less likely to expand to a state with smaller foreign state. The coefficient estimate on \( \text{CommonBorder} \) is positive and significant, suggesting that a BHC is more likely to enter a foreign state with which it shares a common border. The coefficient estimate of the home state dummy is positive and significant, indicating that BHCs are more likely to expand business in its home state. Based on the coefficient estimates in column (3) of Table 2, an increase of 100 miles in distance between a
BHC’s headquarters and a foreign state’s capital leads to a decline of 3.8% deposit share in the foreign state.

——— Insert Table 2 here ———

### 3.3 Two-Stage Least Squares (2SLS) Regression

We obtain the predicted value of deposit share of a BHC in a state from the regression model in column (3) in Table 2. We incorporate the staggered removals of interstate banking restrictions in different states over time by setting the predicted values to zero for those BHC-state pairs in which the BHC is restricted from operating in the foreign state. We then compute the Herfindahl index of each BHC based on the dispersion of the predicted values of deposit shares across all states (*Predicted HHI*). Finally we construct the predicted diversification measure for each BHC in a year as *1−*Predicted HHI, which serves as an instrument variable for the actual geographic diversification measure *1- HHI*.

To investigate the causal relationship between bank geographic diversification and borrowing firms’ innovation activities, we employ an instrumental variable approach by estimating the following two equations simultaneously using a two-stage least squares (2SLS) regression framework:

\[
(1−HHI)_{bkt} = \alpha_1 + \beta_1(1−Predicted\ HHI)_{bkt} + \gamma_1 X_{k,t} + \delta_m + \eta_t + \epsilon_{bkt} 
\]  

(3)

\[
Innovation_{b,k,t+n} = \alpha_2 + \beta_2(1−HHI)_{k,t} + \gamma_2 X_{k,t} + \delta_m + \eta_t + \pi_{bkt} 
\]  

(4)

Our sample includes BHC(b)-firm(k)-year(t) observations where each firm (k) is linked to one or multiple BHCs (b) through bank loan contracts. *(1-HHI)* is the actual geographic diversification measure based on a BHC b’s actual deposit dispersion across all states in year t; *(1-Predicted HHI)* is the instrumental variable based on the aforesaid gravity-deregulation model.
Innovation_{bk,t+n} is the innovation variable of firm $k$, which borrows from BHC $b$ in year $t+n$. Given the long duration of innovation projects, we investigate the effect of bank diversification on innovation activities in subsequent years of $t+1$, $t+2$, $t+3$. $X_{kt}$ is a set of firm-specific control variables discussed in Section 2.2.3, including $\ln(Sales)$, $PPE$, $CAPXY$, $ROA$, $Leverage$, $Tobin\ Q$, $H$-$index$, $H$-$index^2$, $KZ\ Index$, and $\ln(age)$. In addition, $\delta_m$ stands for industry fixed effects based on 2-digit SIC codes for industry $m$ and $\eta_t$ is for year fixed effects.

IV. Empirical Results

4.1 Ordinary Least Square (OLS) Results

We first assess the relationship between bank geographic diversification and firm innovation by estimating equation (4) using the conventional OLS technique, where the dependent variables are $\ln(1+Pat)$ and $\ln(1+Cite)$, and the independent variable is $1-HHI$, the actual geographic diversification measure based on deposit dispersion across all states. Results are reported in Table 3. The coefficient estimates on $1-HHI$ are positive yet insignificant in all models, suggesting that bank diversification is not related to firm innovation output as measured by patent counts and citation counts per patent, leading up to three subsequent years. A word of caution is that, bank geographic diversification is endogenous so the coefficient estimates from the OLS models could be biased. Thus we employ an instrumental variable approach to address the endogeneity issue in the next section.

Most control variables display signs as expected. Specifically, innovation is higher in larger and older firms, firms with larger capital expenditures and greater growth opportunity, and firms in more competitive product market. On the other hand, firms with higher asset tangibility and larger leverage ratio, and more profitable firms innovate less.
4.2 Two-Stage Least Squares (2SLS) Results

4.2.1 Innovation Output: Patent Counts and Patent Citations

To address the endogeneity issue due to omitted variables and probe the causal relationship between bank geographic diversification and borrowing firms’ innovation activities, we employ an instrumental variable approach and estimate bank geographic diversification and corporate innovation models simultaneously using a 2SLS framework as described in Section 3. The second-stage model explaining the innovation variables (Eq. 4) is presented in Panel A of Table 4, where the dependent variables are $\text{Ln}(1+\text{Pat})$ and $\text{Ln}(1+\text{Cite})$. The coefficient estimate on $(1-\text{HHI})$ is positive and significant (at 5% or better) across all six models, except in column (6) explaining citation counts per patent in year $t+3$. The result suggests that bank geographic diversification leads to an increase in both innovation quantity and quality in the borrowing firms in the subsequent three years. The results are also economically significant. For instance, as it moves from the 25th to the 75th percentile, $(1-\text{HHI})$ increases by 0.583, which leads to an increase of 2.26 in patent counts and an increase of 4.46 in number of citations per patent in the subsequent year $t+1$.\(^{10}\) As in the OLS results in Table 3, the signs on the control variables are mostly consistent with our expectation.

We report the first stage model explaining bank geographic diversification $(1-\text{HHI})$ in Panel B of Table 4. The instrument $(1-\text{Predicted HHI})$, is significantly and positively related to

--- Insert Table 3 here ---

\(^{10}\) The economic magnitudes are computed based on the coefficient estimates on $(1-\text{HHI})$ in columns (1) and (4). For example, the coefficient estimate of $1-\text{HHI}$ in column (1) is 2.028, we multiple it by 0.583 obtaining 1.182. Since the dependent variable is $\text{Ln}(1+\text{Pat})$, the increase in patent number is $\exp(1.182)-1=2.26$. The increase in citation counts is calculated in the same way.
the geographic diversification measure \((1-HHI)\), satisfying the relevance requirement for an instrument. In addition, our instrument passes both the under-identification and weak identification tests. Take the column (1) in Panel A as an example, the under-identification test with Kleibergen-Paap rk LM statistic is 394.53 (p-value < 1%), and the weak identification test with Cragg-Donald Wald F statistic is 492.28, much greater than the critical value of 16.38 for the 10% maximal IV size based on Stock and Yogo (2005).

As a robustness check, we estimate a reduced form model where we regress the innovation variables against the instrument variable \((1-Predicted \text{ HHI})\) directly, along with the same set of control variables. Results are reported in Panel C of Table 4. Consistent with the 2SLS regression results in Table 4, the coefficient on \((1-Predicted \text{ HHI})\) in the reduced form regression remains positive and significant in all the models except in column (6), indicating that bank geographic diversification enhances both the quantity and quality of innovation in borrowing firms.

4.2.2 Innovation Input: R&D Stock and R&D Expenses

We next investigate how bank geographic diversification affects borrowing firms’ innovation input — R&D stock and R&D expenses. To be consistent with analyses on patent and citation counts, we take natural logarithm of one plus R&D stock \((Ln(1+R&D \text{ stock}))\), and one plus R&D expenses \((Ln(1+R&D \text{ expenses}))\) in years \(t+1, t+2, t+3\), as the dependent variables in the 2SLS regressions. We report the results on \(Ln(1+R&D \text{ stock})\) and \(Ln(1+R&D \text{ expenses})\) in columns (1) – (3) and columns (4) – (6) of Table 5, respectively. The variable of interest, bank geographic diversification \((1-HHI)\), is positively and significantly related to all measures of innovation input, except in column (6). The result indicates that bank geographic diversification...
boosts borrowing firms’ investments in R&D activities, leading to increased innovation output measured by patent counts and citation counts per patent.

4.2.3 Innovation scope

We next examine the impact of bank geographic diversification on innovation scope. To the extent that geographic diversification enables banks to reduce idiosyncratic risk as documented in Goetz, Laeven, and Levine (2016), banks might be more tolerant as borrowing firms taking greater risk by exploring brand new innovative projects that are unrelated to their core business.

For this purpose, we identify the number of patents that are related or unrelated to a firm’s core business. The US Patent and Trademark Office (USPTO) assigns each patent to a three-digit technology class, which we map to one or multiple two-digit SIC codes using a concordance table developed by Hsu, Tian, and Xu (2014). A firm’s patents that can be mapped to its main two-digit SIC code are defined as related patents, and the rest of patents are defined as unrelated patents. We then compute the number of related patents that can be mapped to the firm’s main two-digit SIC code by multiplying patent counts by the corresponding mapping weights (Related). The number of unrelated patents is obtained by subtracting the number of related patents from total patent counts for each firm (Unrelated). Related patents indicate the firm focus their innovation on core business, while unrelated patents indicate the firm expand their innovation scope to other business lines.

Similar to other innovation variables, we take a natural logarithm of one plus the number of unrelated patents, and one plus the number of related patents in years t+1, t+2, t+3, and use them as dependent variables to probe the effect of bank geographic diversification on firm
innovation scope. Results are reported in columns (1) – (3) for Ln(1+ Unrelated patents), and columns (4) – (6) for Ln(1+ Related patents) in Table 6. We find that bank geographic diversification is positively and significantly (at 5%) related to unrelated patents in the subsequent two years, as in columns (1) and (2). In contrast, we find little significant effect of bank geographic diversification on the number of related patents. The results suggest that bank diversification enables firms to expand their innovation scope to explore innovation projects beyond their core business. Therefore the increased patent counts associated with bank geographic diversification documented above appear to be driven by an increase in unrelated patents.

4.2.4 Innovation Search Strategy

To provide a richer picture of how bank geographic diversification affects innovation, we explore the innovation search strategy in unknown technology areas. Following Balsmeier, Fleming, and Manso (2017) we construct two measures of innovation search strategy. The first measure Unknown is the natural logarithm of one plus the number of patents filed in technology classes that are previously unknown to the firm. The second measure Techproximity assesses the technological proximity between the patents filed in year t and the existing patent portfolio held by the same firm up to the previous year, hence computed based on the following formula:

\[
Techproximity_{it} = \sum_{k=1}^{K} f_{ikt} f_{ikt-1} \left( \frac{\sum_{k=1}^{K} f_{ikt}^2 \cdot \sum_{k=1}^{K} f_{ikt-1}^2}{\sum_{k=1}^{K} f_{ikt}^2 \cdot \sum_{k=1}^{K} f_{ikt-1}^2} \right)^{1/2}
\]

where \( f_{ikt} \) is the proportion of firm i’s patents that belong to technology class k in year t, and \( f_{ikt-1} \) is the proportion of firm i’s patent portfolio up to the previous year that belongs to technology class k. \( P_{it} \) is bound between zero and one. Techproximity equals one if the patents filed in year t
are distributed across technology classes in exactly the same way as the existing patent portfolio owned by the same firm up to the year before. A greater (smaller) value of Techproximity indicates more exploitative (explorative) innovations within known (unknown) technology areas.

2SLS regression results are presented in Table 7. The coefficient estimate on $\ln(1 + \text{Unknown})$ is positive and significant at the 1% level in all three columns, suggesting that bank geographic diversification enables firms to launch more innovative activities in unknown areas. The coefficient estimate on Techproximity is negative and significant at the 5% level in all columns, indicating that bank diversification leads borrowing firms to take on more exploratory innovation projects that are different from their existing patents.

——— Insert Table 7 here ———

4.2.5 Economic Value of Innovation

While patent citations reveal the scientific value of innovation, they do not offer much information on the private rents a patent may generate for a firm. To shed light on this, we follow Kogan et al. (2017) and employ a measure of economic value of each patent that is based on stock market reaction to announcements of patent grants. More specifically, the economic value of a patent is computed by multiplying the stock market abnormal return in response to the announcement of patent grant by the market cap of the firm on the day prior to the announcement day of patent grant.

We obtain the patent value data from Professor Noah Stoffman’s website.\textsuperscript{11} Since many firms hold multiple patents in a given year, we compute the average of economic value of those

\textsuperscript{11} We thank Professor Stoffman for graciously making the patent data publicly available at https://iu.app.box.com/v/patents.
patents \( (\text{Patent\_value\_avg} ) \) and the sum of the economic value of all patents \( (\text{Patent\_value\_sum} ) \).

We then examine how bank diversification affects the values of patents produced by their borrowing firms. The dependent variables are the natural logarithm of one plus \( \text{Patent\_value\_avg} \) or one plus \( \text{Patent\_value\_sum} \) in years \( t+1, t+2, t+3 \), with results reported in columns (1) - (3) and columns (4) - (6) of Table 8, respectively.

Columns (1) and (2) of Table 8 show that bank geographic innovation leads to significantly higher average economic value per patent in years \( t+1 \) and \( t+2 \). Results in columns (4) and (5) show that bank geographic innovation also enhances the total economic value of patents in subsequent two years. By exploratory innovation activities that are unrelated to firms’ main business and innovation search in unknown areas, firms extract larger private rents via innovation since the innovation activities unrelated to their core business and those in unknown area enable the firms to expand their business boundary and explore better business opportunities in the competitive environment.

To sum up, bank geographic diversification boosts borrowing firms’ R&D expenses and corporate innovation output as measured by both patent counts and citation counts, enables firms to expand innovation scope by exploring innovation activities beyond their core business, and extend their search strategy in unknown areas, all of which contributing to a greater economic value of innovation.

——— Insert Table 8 here ———

4.3. Channels of Effects

In this section we explore debt covenants and financial constraints as two potential channels through which bank geographic diversification affects corporate innovation.
4.3.1 Debt Covenants Channel

Jensen and Meckling (1976) suggest that the risk-shifting incentive of equity-holders may prompt creditors to restrict investments through debt covenants. Nini, Smith, and Sufi (2009) find that 32% of the debt contracts contain an explicit restriction on capital expenditures, which leads to a reduction in firm investments. The effects of binding covenants on borrowers are substantial, ranging from limited access to otherwise committed credit facilities (Sufi 2009) to increased lender influence over the real and financial decisions of the firm (Beneish and Press 1993; Chava and Roberts 2008; Nini, Smith, and Sufi 2009, 2012; Roberts and Sufi 2009a, 2009b).

While it is quite common for debt contracts to contain covenants restricting capital expenditures, contracts generally do not contain covenants explicitly restriction on firms’ innovation activities. Nevertheless, a majority of debt covenants are tied to a firm’s Debt/EBITDA ratio and net worth. Because innovation input, such as R&D, is expensed immediately, which reduces a firm’s EBITDA and net worth. Hence, although debt covenants do not directly restrict R&D spending, firms might still be forced to curtail their innovation activities to meet debt covenant thresholds. As a result, more covenants and tighter covenants could force borrowing firms to switch their long-term investments in innovation to less risky, short-term ones that can generate more stable cash flows, which naturally results in a cut in innovation.

Prior literature documents that debt contract terms are related to banks’ financial condition. For example, Murfin (2012) find that banks experienced loan defaults write tighter debt contracts than their peers do, even when defaulting borrowers are in different industries and different geographic regions from the current borrower. The evidence suggests that recent defaults inform a lender about its own screening ability, thereby impacting its contracting behavior. To the extent that bank geographic diversification reduces credit risk, diversified banks may offer bank loans to
borrowing firms on more amenable terms (i.e., fewer number of covenants and less stringent covenants). Kahan and Yermack (1998) find a negative relation between investment opportunities and the use of debt covenants, suggesting that in the presence of ample investment opportunities, debtholders might not want to use covenants to tie managers’ hands to avoid ruling out potential valuable strategies. Fewer and less stringent covenants may reduce lenders influence over the real and financial decisions of the firm, especially when borrowers have valuable investment opportunities, spurring innovation activities.

To test the above conjecture, we construct multiple measures of the degree of covenant strictness, including number of general covenants, number of financial covenants, number of capital covenants, number of performance covenants\(^\text{12}\), and covenant strictness. Christensen and Nikolaev (2012) argue that capital covenants (e.g., leverage, net worth, etc.) alleviate agency problems by aligning the interests of creditors with those of shareholders, while performance covenants (e.g., debt-to-EBITDA, interest coverage, etc.) serve as trip wires that curb agency problems by allocating control rights to lenders in states where creditors’ claims are at risk. While capital covenants restrict the amount of resources a borrower can invest, they do not necessarily limit the riskiness of the investment. In contrast, performance covenants are tied to the outcome of the investments, which likely dampen borrowers’ incentives to take excessive risk. We follow Murfin (2012) to construct *Covenant strictness*. For a covenant that stipulates a minimum value \( \gamma \) for a financial ratio, \( \gamma \) that is normally distributed with standard deviation \( \sigma \), tightness can be

\(^{12}\text{Capital covenants} \) include minimum quick ratio minimum current ratio, maximum debt-to-equity, maximum debt-to-tangible net worth, maximum leverage, maximum senior leverage, minimum net worth, and minimum tangible net worth. \( \text{Performance covenants} \) include maximum debt-to-EBITDA, minimum EBITDA, minimum current ratio, minimum fixed charge coverage, minimum interest coverage, maximum senior debt-to-EBITDA, minimum cash interest coverage, and minimum debt service coverage.
measured as the probability of a covenant violation: \( P = 1 - \Phi\left(\frac{\gamma_i - \gamma}{\sigma}\right) \). If a loan contains multiple covenants, we follow Prilmeier (2017) and use the average covenant tightness of all covenants in the loan to proxy for covenant strictness.

To investigate the covenant channel, we assess how bank geographic diversification affects the covenants terms in their loan contracts in a 2SLS regression framework. Following Wang and Xia (2014), we include a set of control variables such as B-rated, loan size, maturity, performance pricing, bank liquidity, long term debt to operating income, short term debt to operating income, and credit spread in the model of covenants. Results on the number of financial covenants, number of general covenants, number of performance covenants, number of capital covenants, and covenant strictness are shown in columns (1) – (5) of Table 9. Consistent with our aforesaid conjecture, geographically diversified banks offer loans with significantly fewer financial and general covenants, as well as fewer capital covenants and less strict covenants.

Overall our results lend support to the covenant channel, suggesting that geographically diversified banks tend to offer loans with more pardoning covenant terms, hence exerting less influence over the real and financial decisions of the borrowing firms, which in turn stimulating innovation activities.

——— Insert Table 9 here ———

4.3.2 Financial Constraints Channel

Bank geographic expansion allows out-of-state banks to provide bank loans to corporate firms, which makes it easier for firms to obtain bank credit and hence alleviate their financial constraints. As a result, firms can deploy the much-needed bank credit to launch innovative
projects that may boost corporate innovation. To test this conjecture, we examine how bank geographic expansion affects borrowing firms’ extent of financial constraints. If financial constraint serves as a channel effect, we expect a negative effect of bank diversification on the degree of financial constraint in borrowing firms. We employ two widely used financial constraints measures – the Whited and Wu (2006) index (WWIndex) and the Kaplan and Zingales (1997) index (KZIndex), and regress bank geographic diversification against each measure in the 2SLS regression framework. Detailed variable definition of WWIndex and KZIndex are in Appendix B. Results are tabulated in Table 10. We find bank geographic diversification significantly reduce borrowing firms’ financial constraints as measured by WW Index, supporting our financial constraints channel. Bank geographic diversification also leads borrowing firms to be less financial constrained measured by the KZindex, but the result is insignificant.

4.4 Robustness Checks

4.4.1 Placebo Test with Randomly Assigned Deregulation Year

There is a concern that our results might be driven by an omitted variable that coincides with interstate bank deregulation and affects both bank geographic expansion and corporate innovation. To address this concern, we conduct a placebo (falsification) test in which we randomly assign a deregulation year to each state-pair during 1986 and 1997. That is, we falsely assume a BHC can legally enter a foreign market at a random year between 1986 and 1997. The actual interstate bank deregulation started in 1978 and ended in 1997. Given that our sample period starts in 1986, we randomly assign the deregulation years between 1986 and 1997. We then use the falsely assumed deregulation year for each state-pair to construct the instrumental
variable (1-Predicted HHI) based on the gravity-deregulation model and re-estimate Equations (3)-(4) in a 2SLS framework.

The 2nd stage results explaining the innovation variable are presented in Table 11. We find none of the coefficient estimates on bank geographic diversification is significant, confirming that our results are not likely driven by omitted variable.

--- Insert Table 11 here ---

4.4.2 Alternative Model of Constructing the Instrumental Variable

Our gravity-deregulation model is an improved version of the model in Goetz, Laeven, and Levine (2013, 2016) by incorporating a common land border variable and home state dummy to account for the possibility that a BHC is more likely to expand to a foreign state which shares a common border with its home state, and a BHC may expand business to a greater extent within its home state, respectively. To check the robustness of our results, nonetheless we follow Goetz, Laeven and Levine (2013, 2016) more closely and use the following model to construct the instrumental variable:

\[
Share_{bijt} = \alpha \ln(\text{Distance}_{bij}) + \beta \ln(GSP_{it}/GSP_{jt}) + \epsilon_{bijt},
\]

where \(Share_{bijt}\) is the percentage of BHC \(b\)’s deposits in all subsidiaries in state \(j\) in year \(t\) and BHC \(b\) is headquartered in state \(i\). \(\text{Distance}_{bij}\) is the straight-line distance between BHC \(b\)’s headquarter location in state \(i\) and the capital of state \(j\). \(\ln(GSP_{it}/GSP_{jt})\) is the natural logarithm of the ratio of Gross State Product (GSP) of BHC \(b\)’s home state \(i\) and that of a foreign state \(j\) in year \(t\). We use the predicted shares from Equation (6) to calculate Predicted HHI, and then use 1-Predicted HHI as instrument for actual geographic diversification (1-HHI). We employ the instrumental variable.
based on Equation (6) and estimate models (3) and (4) simultaneously using a 2SLS technique. The 2nd stage results from the 2SLS regressions are shown in Panel A of Table 12. Bank geographic diversification remains a significant positive driving force behind corporate innovation activities measured by both the quantity and quality of innovation.

4.4.3 Alternative Measure of Geographic Diversification

In the main results, we use deposit dispersion across state as the main proxy for bank geographic diversification. Alternatively we compute asset dispersion across state as an alternative measure of bank geographic diversification. Results are reported in Panel B of Table 12. The coefficient on \((1 - HHI)\) is positive and significant at the 5\% level or higher in all models, confirming the robustness of our results using deposit dispersion.

4.4.4 Subsample Containing Lead Banks Only

Prior studies on bank loan contracting mostly focus on lead banks of a syndicated loan (e.g., Graham, Li, and Qiu 2008; Deng, Willis, and Xu 2014; Campello and Gao 2017). In our main analyses we retain both lead and participant banks in a syndicate as we argue the credit supply by both types of banks may influence corporate innovation. As a robustness check, we only retain the borrower-lead bank pairs in the sample. The results, as reported in Panel C of Table 12, are qualitatively similar as before, despite that the sample size is reduced by half.

4.4.5 Estimating the 1st Stage and 2nd Stage Models Separately

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14 Chen and Vashishtha (2017) also use repeated values in their analysis. Their unit of analysis is at the contract-bank-quarter level, those sample firms with multiple loan contracts and firms with multiple lead banks in a syndicated loan will appear multiple times in the sample for a given quarter.
When a firm borrows from multiple lenders, there could be repeated dependent variables of innovation variables that may bias the results. To address this concern, we first estimate stage one model of bank geographic diversification separately to obtain the predicted value of \((1 - HHI)\), then we use the max of fitted value of \((1 - HHI)\) in the second stage model of corporate innovation, in this way we retain only one lender with the largest predicted value of \((1 - HHI)\) for each borrowing firm. The results are reported in Panel D of Table 12, indicating that the bank geographic diversification spurs corporate innovation measured by both patent and citation counts.

V. Conclusion

By exploiting the interstate bank deregulation as an exogeneous shock to bank geographic expansion, we examine the causal relationship between bank geographic diversification and corporate innovation. We do so by integrating the staggered interstate bank deregulation into a gravity model that projects a BHC’s expansion to a foreign state, based on which we construct an exogenous time-varying BHC-specific instrumental variable for bank geographic diversification following Goetz, Laeven, and Levine (2013, 2016). This approach allows us to disentangle the effect of bank deregulation on bank geographic diversification and competition. We also link banks with borrowing firms through bank loan contracts and investigate a direct causal effect of the extent of banks' geographic diversification on the innovation activities of their borrowers.

Empirical results show that bank geographic diversification boosts borrowing firms’ R&D expenses, stimulates corporate innovation activities as measured by both the number of patents a

\[15 \text{ We also tried to use the average fitted value of } (1 - HHI) \text{ from first stage model if a firm borrow from multiple banks in a given year. Results are qualitatively similar though less significant.}\]
firm has and the number of non-self-citations a patent receives, enables firms to expand innovation scope by developing lines of business that are unrelated to their core business, and extend innovation search to unknown areas, all of which enhance innovation economic value. The results are robust to several robustness checks including placebo test, and instrumental variable based on alternative gravity-deregulation model, alternative geographic diversification measure, keep lead banks only, and other estimation techniques.

Furthermore, we explore diversified banks offering bank loans with less stringent covenants and bank credit alleviating borrowers’ financial constraints as two potential channels that explain the documented relationship between bank geographic diversification and corporate innovation. We find diversified banks offer bank loans with more pardoning terms, i.e., fewer covenants and less stringent covenants, which reduce the likelihood of lender intervention in firms’ investment and financing activities, and hence are conducive to corporate innovation. Furthermore, bank geographic expansion enable borrowing firms to obtain more bank credit supply, which alleviates borrowers’ financial constraints and promotes corporate innovation.
References


Table 1: Summary statistics
This table provides summary statistics for our sample during the sample period between 1986 and 2006. Panel A is for firm-specific variables, with observations uniquely identified by firm-year. Panel B is BHC-specific variables, with observations uniquely identified by BHC-year. A firm may borrow from multiple BHCs in a given year, and a BHC may lend to multiple firms in a given year. Our final sample contains 3449 firms borrowing from 153 unique BHCs.

<table>
<thead>
<tr>
<th>Panel A. Firm-specific Variables</th>
<th>N</th>
<th>Mean</th>
<th>Sd</th>
<th>Max</th>
<th>Min</th>
<th>P25</th>
<th>P50</th>
<th>P75</th>
</tr>
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<tr>
<td>Patt+1</td>
<td>11,887</td>
<td>17</td>
<td>98.82</td>
<td>3,798.00</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>2</td>
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<td>Cite_{t+1}</td>
<td>11,887</td>
<td>4.731</td>
<td>11.87</td>
<td>235.8</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>4.258</td>
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<tr>
<td>R&amp;Dstock_{t+1} ($million)</td>
<td>11,887</td>
<td>120.6</td>
<td>335.1</td>
<td>1,597.00</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>46.6</td>
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<td>R&amp;D_{t+1} ($million)</td>
<td>11,887</td>
<td>43.02</td>
<td>117.9</td>
<td>557</td>
<td>0</td>
<td>0</td>
<td>0</td>
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<tr>
<td>Related_{t+1}</td>
<td>11,887</td>
<td>2.146</td>
<td>6.456</td>
<td>29.14</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.14</td>
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<tr>
<td>Unrelated_{t+1}</td>
<td>11,887</td>
<td>4.916</td>
<td>13.68</td>
<td>61.51</td>
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<td>0</td>
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<td>Unknown_{t+1}</td>
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<td>0</td>
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<td>Patent_value_avg ($million)</td>
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<td>7.279</td>
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<td>0</td>
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<td>230.5</td>
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<td>3.417</td>
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<td>Ln(Sales)</td>
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<td>6.493</td>
<td>1.942</td>
<td>10.91</td>
<td>2.807</td>
<td>5.078</td>
<td>6.447</td>
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<td>0.882</td>
<td>0.005</td>
<td>0.125</td>
<td>0.239</td>
<td>0.412</td>
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<td>0.199</td>
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<td>0.135</td>
<td>0.268</td>
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<td>Tobin Q</td>
<td>11,886</td>
<td>1.763</td>
<td>1.089</td>
<td>6.676</td>
<td>0.651</td>
<td>1.106</td>
<td>1.418</td>
<td>1.996</td>
</tr>
<tr>
<td>H-index</td>
<td>11,887</td>
<td>0.067</td>
<td>0.062</td>
<td>0.413</td>
<td>0.008</td>
<td>0.036</td>
<td>0.046</td>
<td>0.074</td>
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<td>H-index^2</td>
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<td>0.022</td>
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<td>0.001</td>
<td>0.002</td>
<td>0.005</td>
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<td>83.93</td>
<td>-41.75</td>
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<td>4.025</td>
<td>0.693</td>
<td>1.946</td>
<td>2.773</td>
<td>3.584</td>
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<th>Sd</th>
<th>Max</th>
<th>Min</th>
<th>P25</th>
<th>P50</th>
<th>P75</th>
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<td>0.302</td>
<td>0.919</td>
<td>0</td>
<td>0</td>
<td>0.246</td>
<td>0.583</td>
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<td># of Operating States</td>
<td>1,031</td>
<td>4.661</td>
<td>4.984</td>
<td>33</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>6</td>
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<tr>
<td># of Operating Branches</td>
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<td>354.1</td>
<td>629.1</td>
<td>5588</td>
<td>1</td>
<td>30</td>
<td>134</td>
<td>392</td>
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</table>
Table 2. Gravity-deregulation model

This table reports results based on the gravity-deregulation model. Following Goetz et al. (2013) we first estimate the following model to project the deposit share a BHC has in a foreign state using fractional logit regression:

\[ \text{Share}_{bij} = \beta_1 \text{Distance}_{bij} + \beta_2 \ln \left( \frac{\text{GSP}_i}{\text{GSP}_j} \right) + \beta_3 \text{CommonBorder}_{ij} + \beta_4 \text{HomeStat}_i + \epsilon_{bij}, \]

where the dependent variable \( \text{Share}_{bij} \) is the percentage of BHC \( b \)'s deposits in state \( j \) in a quarter \( t \) and BHC \( b \) is headquartered in state \( i \). \( \text{Distance}_{bij} \) is the straight-line distance between BHC \( b \)'s headquarter in state \( i \) and the capital of state \( j \). \( \text{GSP}_i \) is Gross State Product (GSP) of a BHC’s home state \( i \) in quarter \( t \), while \( \text{GSP}_j \) is the GSP of a foreign state \( j \) to which the BHC \( b \) allocates its assets in quarter \( t \). \( \text{CommonBorder}_{ij} \) is an indicator variable that equals to one if state \( i \) and state \( j \) share a common land border. \( \text{HomeStat}_i \) is a dummy variable that equals to one if a BHC receives deposits in the home state \( i \). The coefficients report average marginal effects based on fractional Logit model. Standard errors are clustered at state-year level. T-values are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

<table>
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<th>Predicted sign</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
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<tbody>
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<td>( \text{Distance} )</td>
<td>-0.0248***</td>
<td>-0.0113***</td>
<td>-0.0038***</td>
</tr>
<tr>
<td>( \text{Ln(GSP}_i/\text{GSP}_j) )</td>
<td>-0.0086***</td>
<td>-0.0016***</td>
<td></td>
</tr>
<tr>
<td>( \text{CommonBorder} )</td>
<td>+0.0028***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \text{HomeState} )</td>
<td>+0.0277***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( N )</td>
<td>428,343</td>
<td>428,343</td>
<td>428,343</td>
</tr>
</tbody>
</table>
Table 3. Bank geographic diversification and corporate innovation output — OLS regression

This table shows the OLS results. The dependent variables are patent and citation counts. Patent count is proxied by \( \ln(1+\text{Pat}) \), which is the natural logarithm of one plus total number of patents filed (and eventually granted) in years \( t+1, t+2, \) and \( t+3 \), with results reported in columns (1)–(3), respectively; Citation count is proxied by \( \ln(1+\text{Cite}) \), which is the natural logarithm of one plus total number of non-self-citations received per patent in years \( t+1, t+2, t+3 \), with results reported in columns (4)–(6), respectively. The independent variable of interest is \( 1-\text{HHI} \), which is one minus Herfindahl index of deposits across states. We use heteroskedasticity-robust standard errors and report t-values in parentheses. *, ** and *** denote statistical significance at 10%, 5% and 1%, respectively.

<table>
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<tr>
<th></th>
<th>( t+1 )</th>
<th>( t+2 )</th>
<th>( t+3 )</th>
<th>( t+1 )</th>
<th>( t+2 )</th>
<th>( t+3 )</th>
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</thead>
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<tr>
<td>( 1-\text{HHI} )</td>
<td>0.088</td>
<td>0.048</td>
<td>0.03</td>
<td>0.221</td>
<td>0.224</td>
<td>0.25</td>
</tr>
<tr>
<td></td>
<td>(0.962)</td>
<td>(0.434)</td>
<td>(0.225)</td>
<td>(1.057)</td>
<td>(0.841)</td>
<td>(0.886)</td>
</tr>
<tr>
<td>( \ln(\text{Sales}) )</td>
<td>0.349***</td>
<td>0.324***</td>
<td>0.299***</td>
<td>0.497***</td>
<td>0.447***</td>
<td>0.415***</td>
</tr>
<tr>
<td>( \text{PPE} )</td>
<td>-0.334***</td>
<td>-0.312***</td>
<td>-0.234***</td>
<td>-0.655***</td>
<td>-0.572***</td>
<td>-0.466***</td>
</tr>
<tr>
<td></td>
<td>(-5.891)</td>
<td>(-5.223)</td>
<td>(-4.344)</td>
<td>(-7.475)</td>
<td>(-5.345)</td>
<td>(-5.036)</td>
</tr>
<tr>
<td>( \text{CAPX} )</td>
<td>1.693***</td>
<td>1.606***</td>
<td>1.382***</td>
<td>2.638***</td>
<td>2.901***</td>
<td>2.424***</td>
</tr>
<tr>
<td>( \text{ROA} )</td>
<td>-0.202***</td>
<td>-0.242***</td>
<td>-0.182***</td>
<td>-0.156**</td>
<td>(0.148)</td>
<td>(0.137)</td>
</tr>
<tr>
<td></td>
<td>(-4.642)</td>
<td>(-4.611)</td>
<td>(-3.068)</td>
<td>(-2.174)</td>
<td>(-1.567)</td>
<td>(-1.565)</td>
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<tr>
<td>( \text{Leverage} )</td>
<td>-0.362***</td>
<td>-0.364***</td>
<td>-0.314***</td>
<td>-0.616***</td>
<td>-0.554***</td>
<td>-0.477***</td>
</tr>
<tr>
<td></td>
<td>(-10.867)</td>
<td>(-9.792)</td>
<td>(-7.363)</td>
<td>(-10.250)</td>
<td>(-8.826)</td>
<td>(-6.666)</td>
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<td>( \text{Tobin Q} )</td>
<td>0.042*</td>
<td>0.042*</td>
<td>0.037</td>
<td>0.064*</td>
<td>0.061*</td>
<td>0.049</td>
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<td></td>
<td>(1.803)</td>
<td>(1.721)</td>
<td>(1.651)</td>
<td>(1.784)</td>
<td>(1.716)</td>
<td>(1.639)</td>
</tr>
<tr>
<td>( \text{H-index} )</td>
<td>0.925***</td>
<td>1.387***</td>
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<td>2.885***</td>
<td>4.363***</td>
<td>7.120***</td>
</tr>
<tr>
<td></td>
<td>(3.564)</td>
<td>(3.618)</td>
<td>(5.335)</td>
<td>(4.862)</td>
<td>(7.600)</td>
<td>(9.608)</td>
</tr>
<tr>
<td>( \text{H-index}^2 )</td>
<td>-1.179***</td>
<td>-2.604***</td>
<td>-4.896***</td>
<td>-4.856***</td>
<td>-8.657***</td>
<td>-15.676***</td>
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<td>(-2.219)</td>
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<td>(-4.202)</td>
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<td>0.000*</td>
<td>0.000*</td>
<td>0.000*</td>
<td>0.000*</td>
<td>0.000*</td>
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<td></td>
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<td>0.089***</td>
<td>0.069***</td>
<td>0.129***</td>
<td>0.115***</td>
<td>0.084***</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>( \text{Year fixed effects} )</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>( N )</td>
<td>36,126</td>
<td>34,298</td>
<td>32,569</td>
<td>36,126</td>
<td>34,298</td>
<td>32,569</td>
</tr>
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</table>
Table 4: Bank geographic diversification and innovation output – 2SLS regressions

This table reports 2SLS regression results on how bank geographic diversification affects corporate innovation output. Panel A reports the second-stage results on innovation output. The dependent variable \( \ln(1+\text{Pat}) \) is the natural logarithm of one plus total number of patents filed (and eventually granted) in years \( t+1, t+2, t+3 \), with results reported in columns (1)–(3), respectively; Dependent variable \( \ln(1+\text{Cite}) \) is the natural logarithm of one plus total number of non-self-citations received per patent in years \( t+1, t+2, t+3 \), with results reported in columns (4)–(6), respectively. Independent variable of interest is bank geographic diversification \( (1-HHI) \), which is the predicted value of one minus Herfindahl Index of bank deposits across states based on stage one model of bank geographic diversification. Panel B reports the results of first-stage model of bank geographic diversification with the instrument variable being one minus the Predicted value of \( HHI \) based on the gravity-deregulation model. All other variables are defined in Appendix B. We use heteroskedasticity-robust standard errors and report t-values in the parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

<table>
<thead>
<tr>
<th></th>
<th>( \ln(1+\text{Pat}) )</th>
<th>( \ln(1+\text{Cite}) )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( t+1 )</td>
<td>( t+2 )</td>
</tr>
<tr>
<td>( 1-HHI )</td>
<td>2.028***</td>
<td>1.954***</td>
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<tr>
<td></td>
<td>(3.358)</td>
<td>(3.159)</td>
</tr>
<tr>
<td>( \ln(\text{Sales}) )</td>
<td>0.374***</td>
<td>0.349***</td>
</tr>
<tr>
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<td>(42.562)</td>
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<td>( \text{PPE} )</td>
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<td>-0.335***</td>
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<tr>
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<td>(-6.215)</td>
<td>(-5.648)</td>
</tr>
<tr>
<td>( \text{CAPX} )</td>
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<td>1.422***</td>
</tr>
<tr>
<td>( \text{ROA} )</td>
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<td>-0.510***</td>
</tr>
<tr>
<td></td>
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<tr>
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<td>-0.314***</td>
</tr>
<tr>
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<td>(-7.726)</td>
<td>(-7.215)</td>
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<tr>
<td>( \text{Tobin \ Q} )</td>
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<td>0.048*</td>
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<tr>
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<td>(2.035)</td>
<td>(1.862)</td>
</tr>
<tr>
<td>( H-index )</td>
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<td>1.237***</td>
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<tr>
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<td>(2.824)</td>
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<td>( H-index^2 )</td>
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<td>-2.404***</td>
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<td>0.000</td>
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<td>( \ln(\text{Age}) )</td>
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<td>0.084***</td>
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<td>Yes</td>
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<tr>
<td>( \text{Year fixed effects} )</td>
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<td>Yes</td>
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<td>( \text{Kleibergen-Paap rk LM statistic} )</td>
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<td>( \text{Cragg-Donald Wald F statistic} )</td>
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### Panel B: 2SLS first stage results

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<th>34,298</th>
<th>32,569</th>
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<td>0.17***</td>
<td>0.17***</td>
<td>0.17***</td>
<td>0.17***</td>
<td>0.17***</td>
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<tr>
<td></td>
<td>(6.206)</td>
<td>(5.912)</td>
<td>(5.672)</td>
<td>(6.206)</td>
<td>(5.912)</td>
<td>(5.672)</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<td>Industry fixed effects</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year fixed effects</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<td><strong>N</strong></td>
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### Panel C: Reduced form second stage results

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<th>34,298</th>
<th>32,569</th>
</tr>
</thead>
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<tr>
<td><strong>1- Predicted HHI</strong></td>
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<td>0.33***</td>
<td>0.19**</td>
<td>0.50***</td>
<td>0.34**</td>
<td>0.06</td>
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<td>(2.230)</td>
<td>(3.463)</td>
<td>(2.359)</td>
<td>(0.428)</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Industry fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<td>Year fixed effects</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>36,126</td>
<td>34,298</td>
<td>32,569</td>
<td>36,126</td>
<td>34,298</td>
<td>32,569</td>
</tr>
</tbody>
</table>
Table 5: Bank geographic diversification and innovation input – 2SLS regressions

This table reports second-stage of 2SLS regression results on how bank geographic diversification affects borrowing firms’ innovation input. The dependent variable Ln(1+ R&D stock) is the natural logarithm of one plus R&D stock in years t+1, t+2, t+3, with the results reported in columns (1)–(3), respectively. Dependent variable Ln(1+R&D expenses) is the natural logarithm of one plus R&D stock which is a firm’s R&D expense depreciated over 5 years at a depreciation rate of 20%, over years t+1, t+2, t+3, with the results reported in columns (4)–(6) respectively. Independent variable of interest is bank geographic diversification (1−HHI), which is the predicted value of one minus Herfindahl Index of bank deposits across states based on stage one model of bank geographic diversification, in which the instrument variable is one minus the Predicted value of HHI based on the gravity-deregulation model. All other variables are defined in Appendix B. We use heteroskedasticity-robust standard errors and report t-values in the parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

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<th>Ln(1+R&amp;D stock)</th>
<th>Ln(1+R&amp;D expenses)</th>
</tr>
</thead>
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<tr>
<td></td>
<td>t+1</td>
<td>t+2</td>
</tr>
<tr>
<td>1-HHI</td>
<td>2.232**</td>
<td>2.006**</td>
</tr>
<tr>
<td></td>
<td>(2.436)</td>
<td>(2.168)</td>
</tr>
<tr>
<td>Ln(Sales)</td>
<td>0.609***</td>
<td>0.610***</td>
</tr>
<tr>
<td></td>
<td>(44.443)</td>
<td>(43.931)</td>
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<tr>
<td>PPE</td>
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<td>-1.393***</td>
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<tr>
<td></td>
<td>(-14.697)</td>
<td>(-15.041)</td>
</tr>
<tr>
<td>CAPX</td>
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<td>1.889***</td>
</tr>
<tr>
<td>ROA</td>
<td>-0.956***</td>
<td>-0.770***</td>
</tr>
<tr>
<td></td>
<td>(-7.567)</td>
<td>(-6.462)</td>
</tr>
<tr>
<td>Leverage</td>
<td>-0.828***</td>
<td>-0.818***</td>
</tr>
<tr>
<td></td>
<td>(-12.433)</td>
<td>(-12.529)</td>
</tr>
<tr>
<td>Tobin Q</td>
<td>0.099***</td>
<td>0.103**</td>
</tr>
<tr>
<td></td>
<td>(2.357)</td>
<td>(2.367)</td>
</tr>
<tr>
<td>H-index</td>
<td>0.269</td>
<td>1.092**</td>
</tr>
<tr>
<td></td>
<td>(0.481)</td>
<td>(1.993)</td>
</tr>
<tr>
<td>H-index^2</td>
<td>0.010</td>
<td>-1.270</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(-1.396)</td>
</tr>
<tr>
<td>KZ Index</td>
<td>-0.000</td>
<td>-0.000</td>
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</table>
Table 6: Bank geographic diversification and innovation focus – 2SLS regressions

This table reports second-stage of 2SLS regression results on how bank geographic diversification affects borrowing firms’ innovation focus. The dependent variable $\ln(1+\text{related patents})$ is the natural logarithm of one plus total number of related patents, which can be mapped to a firm’s main two-digit SIC industry, in years $t+1$, $t+2$, $t+3$, with results reported in columns (1)–(3) respectively; The dependent variable $\ln(1+\text{unrelated patents})$ is the natural logarithm of one plus firm’s unrelated patents, which are cannot be mapped to a firm’s main two-digit SIC industry, in years $t+1$, $t+2$, $t+3$, with the results reported in columns (4)–(6), respectively. Independent variable of interest is bank geographic diversification ($1-\text{HHI}$), which is the predicted value of one minus Herfindahl Index of bank deposits across states based on stage one model of bank geographic diversification, in which the instrument variable is one minus the predicted value of $\text{HHI}$ based on the gravity-deregulation model. All other variables are defined in Appendix B. We use heteroskedasticity-robust standard errors and report t-values in the parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

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<td>0.353***</td>
<td>0.309***</td>
<td>0.282***</td>
<td>0.256***</td>
<td>0.221***</td>
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<td>(40.575)</td>
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<td>-0.235***</td>
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<td>0.042**</td>
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<td>(1.999)</td>
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<td>$H-index$</td>
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<td>0.769***</td>
<td>0.382*</td>
<td>0.990***</td>
<td>1.417***</td>
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<td>(2.775)</td>
<td>(1.898)</td>
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<td>(6.807)</td>
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<td>0.000</td>
<td>0.000**</td>
<td>0.000</td>
<td>0.000**</td>
<td>0.000**</td>
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<td>0.095***</td>
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<td>Yes</td>
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<td>Yes</td>
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<tr>
<td>$\text{Year-fixed effects}$</td>
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Table 7: Bank geographic diversification and innovation search strategy in unknown area – 2SLS regressions

This table reports second-stage of 2SLS regression results on how bank geographic diversification affects borrowing firms’ innovation search strategy in unknown area following Balsmeier, Fleming, and Manso (2017). The dependent variable Unknown is the number of patents filed in technology classes that are previously unknown to the firm, over years t+1, t+2, and t+3, with results reported in Column (1) to (3), respectively. The dependent variable Techproximity is continuous measure of the technological proximity between the patents filed in year t and the existing patent portfolio held by the same firm up to the previous year, which is bound between zero and one. A positive coefficient on Techproximity indicates a more exploitative innovation within known areas, while a negative one indicates a more exploratory innovation in unknown areas. Results are reported in Column (4) to (6). Independent variable of interest is bank geographic diversification (1−HHI), which is the predicted value of one minus Herfindahl Index of bank deposits across states based on stage one model of bank geographic diversification, in which the instrument variable is one minus the Predicted value of HHI based on the gravity-deregulation model. We use heteroskedasticity-robust standard errors and report t-values in the parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

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<td>(7)</td>
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<td>0.533***</td>
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<td>-0.062***</td>
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<td>(-1.613)</td>
<td>(-0.778)</td>
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<td>CAPX</td>
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<td>0.063**</td>
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<td>(3.008)</td>
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<td>-0.021**</td>
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<td>0.015**</td>
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<td>(2.823)</td>
<td>(4.205)</td>
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<td>H-index</td>
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<td>H-index^2</td>
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<td>-0.667***</td>
<td>-0.310**</td>
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<tr>
<td>KZ Index</td>
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<td>0.000</td>
<td>-0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>-0.000**</td>
</tr>
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<td>-0.003</td>
<td>0.005**</td>
<td>-0.037***</td>
<td>-0.033***</td>
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<td>(-31.673)</td>
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<td>(-26.864)</td>
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</table>

|                  |         |         |         |         |         |         |
| Industry fixed effects | Yes     | Yes     | Yes     | Yes     | Yes     | Yes     |
| Year fixed effects    | Yes     | Yes     | Yes     | Yes     | Yes     | Yes     |
| N                   | 36,888  | 36,888  | 36,888  | 17,104  | 16,071  | 14,836  |
Table 8: Bank geographic diversification and economic value of patents – 2SLS regressions

This table reports second-stage of 2SLS regression results on how bank geographic diversification affects borrowing firms’ patent economic value. The dependent variable \(\text{Ln}(1+\text{Patent\_value\_avg})\) is the natural logarithm of one plus the average of firm’s patent economic value in years \(t+1, t+2, t+3\), with the results reported in columns (1)–(3), respectively. Patent economic value is obtained by multiplying the abnormal return in the equity market in response to the announcement of patent grant by the market cap on the day prior to patent grant announcement following Kogan et. al. (2017). The dependent variable \(\text{Ln}(1+\text{Patent\_value\_sum})\) is the natural logarithm of one plus the sum of a firm’s patent economic value in years \(t+1, t+2, t+3\), with the results are reported in columns (4)–(6), respectively. Independent variable of interest is bank geographic diversification \((1-\text{HHI})\), which is the predicted value of one minus Herfindahl Index of bank deposits across states based on stage one model of bank geographic diversification, in which the instrument variable is one minus the Predicted value of \(\text{HHI}\) based on the gravity-deregulation model. All other variables are defined in Appendix B. We use heteroskedasticity-robust standard errors and report t-values in the parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

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<th>(\text{Ln}(1+\text{Patent_value_sum}))</th>
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</tr>
<tr>
<td>(\text{N})</td>
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Table 9: Channel effect: debt covenants

This table reports second-stage of 2SLS regression results on the channel effect of covenants of loan contracts. The dependent variables Financial covenant in Column (1) is the number of financial covenants; General covenant in Column (2) is the number of general covenants. Performance covenant in Column (3) is the number of performance covenants; Capital covenants in Column (4) is the number of capital covenants. Covenant strictness in Column (5) is covenant strictness following Murfin (2012). For a covenant that stipulates a minimum value $\gamma$ for a financial ratio, $\gamma$ that is normally distributed with standard deviation $\sigma$, tightness can be measured as the probability of a covenant violation: $P = 1 - \Phi\left(\frac{\gamma - \bar{\gamma}}{\sigma}\right)$. If a loan contains multiple covenants, we follow Prilmeier (2017) and use the average covenant tightness of all covenants in the loan to proxy for covenant strictness. We use fractional logit model in column (5). All other variables are defined in Appendix B. We use heteroskedasticity-robust standard errors and report t-values in the parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

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<td>-0.013**</td>
<td>-0.150***</td>
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<td>B_Rated</td>
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<td>0.756***</td>
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<td>(27.074)</td>
<td>(13.247)</td>
<td>(-10.832)</td>
<td>(18.957)</td>
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<td>Ln(Maturity)</td>
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<td>0.070***</td>
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<td>Performance Pricing</td>
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<td>-0.061*</td>
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<td>ST2CF</td>
<td>0.000</td>
<td>0.000*</td>
<td>0.000</td>
<td>-0.000***</td>
<td>0.005*</td>
</tr>
<tr>
<td></td>
<td>(1.249)</td>
<td>(1.836)</td>
<td>(1.575)</td>
<td>(-2.687)</td>
<td>(1.650)</td>
</tr>
<tr>
<td>Bank Liquidity</td>
<td>0.106***</td>
<td>0.225***</td>
<td>0.180***</td>
<td>-0.074***</td>
<td>0.725***</td>
</tr>
<tr>
<td></td>
<td>(3.366)</td>
<td>(5.018)</td>
<td>(4.927)</td>
<td>(-2.914)</td>
<td>(3.559)</td>
</tr>
<tr>
<td>Credit Spread</td>
<td>-0.149</td>
<td>-0.238</td>
<td>0.200</td>
<td>-0.380***</td>
<td>0.507***</td>
</tr>
<tr>
<td></td>
<td>(-1.021)</td>
<td>(-1.167)</td>
<td>(1.194)</td>
<td>(-3.197)</td>
<td>(7.758)</td>
</tr>
<tr>
<td>Purpose fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Industry fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>N</td>
<td>35,551</td>
<td>35,551</td>
<td>35,551</td>
<td>35,551</td>
<td>16,874</td>
</tr>
</tbody>
</table>
Table 10: Channel effect: financial constraints

This table reports second-stage of 2SLS regression results on how bank geographic diversification alleviates borrowing firms’ financial constraints via extending bank credit. The dependent variables $WW\ Index_{t+1}$ is Whited-Wu(2006) index at time $t+1$. $KZ\ Index_{t+1}$ is Kaplan-Zingales Index at time $t+1$. These two indices measure firms’ financial constraints. Independent variable of interest is bank geographic diversification $(1-HHI)$, which is the predicted value of one minus Herfindahl Index of bank deposits across states based on stage one model of bank geographic diversification, in which the instrument variable is one minus the Predicted value of $HHI$ based on the gravity-deregulation model. All other variables are defined in Appendix B. We use heteroskedasticity-robust standard errors and report t-values in the parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

<table>
<thead>
<tr>
<th></th>
<th>(1) $WW\ Index_{t+1}$</th>
<th>(2) $KZ\ Index_{t+1}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$1-HHI$</td>
<td>-0.06*** (-2.701)</td>
<td>-3.57 (-1.434)</td>
</tr>
<tr>
<td>$Ln(Sales)$</td>
<td>-0.04*** (-86.611)</td>
<td>-0.47*** (-9.591)</td>
</tr>
<tr>
<td>$PPE$</td>
<td>-0.02*** (-5.899)</td>
<td>-8.56*** (-28.008)</td>
</tr>
<tr>
<td>$CAPX$</td>
<td>0.04*** (2.973)</td>
<td>-10.51*** (-11.967)</td>
</tr>
<tr>
<td>$ROA$</td>
<td>-0.03*** (-7.123)</td>
<td>-3.57*** (-3.366)</td>
</tr>
<tr>
<td>$H$-index</td>
<td>-0.01*** (-23.964)</td>
<td>-0.66*** (-12.163)</td>
</tr>
<tr>
<td>$H$-index$^2$</td>
<td>1.04*** (4.141)</td>
<td>37.18** (1.969)</td>
</tr>
<tr>
<td>$Ln(Age)$</td>
<td>-0.01*** (-15.179)</td>
<td>-0.45*** (-3.107)</td>
</tr>
<tr>
<td>Industry fixed effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year fixed effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>N</td>
<td>17,755</td>
<td>17,294</td>
</tr>
</tbody>
</table>
Table 11: Robustness check: Placebo test

This table shows the 2nd stage results of a placebo test. We falsely assign a deregulation year between 1986 and 1997 to a state-pair. That is, we assume a state allows a BHC from another state to enter at a random year between 1986 and 1997. Then we integrate the falsely assigned interstate bank deregulation into the gravity model to project bank geographic expansion across state borders in in stage zero. We use one minus the predicted value of HHI based on the stage zero model (1) as the instrument of \(1-HHI\) and re-estimate model (2) and (3) using 2SLS framework. Independent variable of interest is bank geographic diversification \(\frac{1}{1-HHI}\), which is the predicted value of one minus Herfindahl Index of bank deposits across states based on stage one model of bank geographic diversification, in which the instrument variable is one minus the Predicted value of HHI based on the gravity-deregulation model. We use heteroskedasticity-robust standard errors and report t-values in the parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

<table>
<thead>
<tr>
<th></th>
<th>(t+1)</th>
<th>(t+2)</th>
<th>(t+3)</th>
<th>(t+1)</th>
<th>(t+2)</th>
<th>(t+3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1-HHI)</td>
<td>-34.810</td>
<td>-35.755</td>
<td>132.036</td>
<td>-50.230</td>
<td>-36.306</td>
<td>184.787</td>
</tr>
<tr>
<td>(t+1)</td>
<td>(-0.212)</td>
<td>(-0.157)</td>
<td>(0.049)</td>
<td>(-0.211)</td>
<td>(-0.155)</td>
<td>(0.049)</td>
</tr>
<tr>
<td>(Ln(Sales))</td>
<td>-0.015</td>
<td>-0.086</td>
<td>2.107</td>
<td>-0.051</td>
<td>0.030</td>
<td>2.921</td>
</tr>
<tr>
<td>(t+2)</td>
<td>(-0.008)</td>
<td>(-0.029)</td>
<td>(0.059)</td>
<td>(-0.018)</td>
<td>(0.010)</td>
<td>(0.058)</td>
</tr>
<tr>
<td>(PPE)</td>
<td>-0.311</td>
<td>-0.256</td>
<td>-0.146</td>
<td>-0.616</td>
<td>-0.537</td>
<td>-0.349</td>
</tr>
<tr>
<td>(t+3)</td>
<td>(-0.502)</td>
<td>(-0.275)</td>
<td>(-0.041)</td>
<td>(-0.687)</td>
<td>(-0.561)</td>
<td>(-0.070)</td>
</tr>
<tr>
<td>(t+1)</td>
<td>(0.369)</td>
<td>(0.270)</td>
<td>(-0.042)</td>
<td>(0.374)</td>
<td>(0.341)</td>
<td>(-0.040)</td>
</tr>
<tr>
<td>(t+2)</td>
<td>(0.194)</td>
<td>(0.145)</td>
<td>(-0.050)</td>
<td>(0.199)</td>
<td>(0.146)</td>
<td>(-0.049)</td>
</tr>
<tr>
<td>(Leverage)</td>
<td>-1.382</td>
<td>-1.579</td>
<td>4.231</td>
<td>-2.123</td>
<td>-1.834</td>
<td>5.845</td>
</tr>
<tr>
<td>(t+3)</td>
<td>(-0.294)</td>
<td>(-0.210)</td>
<td>(0.045)</td>
<td>(-0.312)</td>
<td>(-0.238)</td>
<td>(0.044)</td>
</tr>
<tr>
<td>(Tobin\ Q)</td>
<td>-0.053</td>
<td>-0.042</td>
<td>0.370</td>
<td>-0.074</td>
<td>-0.023</td>
<td>0.512</td>
</tr>
<tr>
<td>(t+1)</td>
<td>(-0.112)</td>
<td>(-0.073)</td>
<td>(0.055)</td>
<td>(-0.107)</td>
<td>(-0.039)</td>
<td>(0.055)</td>
</tr>
<tr>
<td>(H-index)</td>
<td>1.425</td>
<td>4.315</td>
<td>-1.979</td>
<td>4.098</td>
<td>8.194</td>
<td>1.956</td>
</tr>
<tr>
<td>(t+2)</td>
<td>(0.392)</td>
<td>(0.274)</td>
<td>(-0.018)</td>
<td>(0.778)</td>
<td>(0.506)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>(H-index^2)</td>
<td>0.799</td>
<td>-5.900</td>
<td>-4.976</td>
<td>-2.821</td>
<td>-13.588</td>
<td>-17.273</td>
</tr>
<tr>
<td>(t+3)</td>
<td>(0.066)</td>
<td>(-0.347)</td>
<td>(-0.094)</td>
<td>(-0.160)</td>
<td>(-0.775)</td>
<td>(-0.234)</td>
</tr>
<tr>
<td>(KZ\ Index)</td>
<td>0.001</td>
<td>0.001</td>
<td>-0.005</td>
<td>0.002</td>
<td>0.002</td>
<td>-0.007</td>
</tr>
<tr>
<td>(t+1)</td>
<td>(0.229)</td>
<td>(0.182)</td>
<td>(-0.046)</td>
<td>(0.255)</td>
<td>(0.208)</td>
<td>(-0.046)</td>
</tr>
<tr>
<td>(Ln(Age))</td>
<td>0.194</td>
<td>0.180</td>
<td>-0.278</td>
<td>0.249</td>
<td>0.204</td>
<td>-0.407</td>
</tr>
<tr>
<td>(t+2)</td>
<td>(0.473)</td>
<td>(0.320)</td>
<td>(-0.039)</td>
<td>(0.420)</td>
<td>(0.352)</td>
<td>(-0.040)</td>
</tr>
<tr>
<td>(Industry\ fixed effects)</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>(Year\ fixed effects)</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>(N)</td>
<td>36,126</td>
<td>34,298</td>
<td>32,569</td>
<td>36,126</td>
<td>34,298</td>
<td>32,569</td>
</tr>
</tbody>
</table>
Table 12: Other robustness checks

This table reports the results of several other robustness tests. In panel A, we use a more concise gravity-deregulation model: $Share_{ijt} = \alpha \ln(Distance_{ijt}) + \beta \ln(GSP_i / GSP_j) + \epsilon_{ijt}$.

Where $Share$ is deposit share in a foreign state; $\ln(Distance)$ is the natural logarithm of one plus the distance between a BHC headquarters and the capital of a foreign state; $\ln(GSP_i / GSP_j)$ is the natural logarithm of the GSP of BHC’s home state $i$ divided by GSP of a foreign state $j$ in time $t$. We use the predicted share from above model to calculate predicted HHI, and then use 1-predicted HHI as the instrument for real HHI in stage one model. In panel B, we use HHI of asset dispersion as an alternative measure of bank geographic diversification. In panel C, we drop observations in which lenders are participant banks, and keep lenders that are lead banks. Standard errors are heteroskedasticity-robust and t-values are reported in parentheses. * *, ** and *** denote statistical significance at 10%, 5% and 1%, respectively.

| Panel A | Alternative instrumental variable | \( Ln(1+Pat) \) & \( Ln(1+Cite) \) |
|---------|-----------------------------------|----------------|----------------|
| \( I-HHI \) | 0.500** | 0.561** | 0.371 | 0.930*** | 0.762** | 0.398 |
| Control Variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| \( N \) | 36,126 | 34,298 | 32,569 | 36,126 | 34,298 | 32,569 |

| Panel B | Alternative geographic diversification measure based on asset dispersion | \( Ln(1+Pat) \) & \( Ln(1+Cite) \) |
|---------|-----------------------------------|----------------|----------------|
| \( I-HHI \) | 1.544*** | 1.561*** | 1.112*** | 2.873*** | 2.409*** | 1.430** |
| Control Variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| \( N \) | 36,558 | 34,707 | 32,960 | 36,558 | 34,707 | 32,960 |

| Panel C | Keep lead banks only | \( Ln(1+Pat) \) & \( Ln(1+Cite) \) |
|---------|---------------------|----------------|----------------|
| \( I-HHI \) | 2.944** | 3.610** | 2.710* | 5.229** | 5.191** | 2.952 |
| Control Variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| \( N \) | 18,569 | 17,586 | 16,672 | 18,569 | 17,586 | 16,672 |

| Panel D | Estimate stage one and stage two models separately | \( Ln(1+Pat) \) & \( Ln(1+Cite) \) |
|---------|---------------------------------------------------|----------------|----------------|
| \( Max(I-HHI) \) | 0.420* | 0.464* | 0.684** | 0.794* | 0.857* | 1.268*** |
| Control Variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| \( N \) | 10,804 | 10,161 | 9,539 | 10,804 | 10,161 | 9,539 |
Appendix A: Sample construction

<table>
<thead>
<tr>
<th>Step</th>
<th>Sample construction process</th>
<th># of facilities/banks/firms</th>
<th># of observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Starting with the lendershares dataset in Dealscan</td>
<td>188,245 facility</td>
<td>1,048,575</td>
</tr>
<tr>
<td>2</td>
<td>Lenders’ names in Dealscan are manually matched to the BHC names among which each BHC has a unique identifier RSSD9001.</td>
<td>122,325 facility, 297 BHCs (RSSD 9001)</td>
<td>350,569</td>
</tr>
<tr>
<td>3</td>
<td>Loan facilities associated with lenders from step 2 are then merged with the Dealscan and COMPUSTAT link file provided by Professor Michael Roberts such that each facility is linked to a Compustat gvkey.</td>
<td>68,331 facility, 10,947 firms (gvkey)</td>
<td>229,851</td>
</tr>
<tr>
<td>4</td>
<td>Use FDIC’s Summary of Deposits to construct the deposit dispersion across states for each BHC. Then merge the deposit dispersion data with the BHC database by RSSD9001 and year.</td>
<td>963 BHCs</td>
<td>9,135</td>
</tr>
<tr>
<td>5</td>
<td>Merge the loan dataset in step 3 with the BHC-related dataset in step 4 based on BHC identifier RSSD9001, and restrict the sample period between 1986 and 2006.</td>
<td>55,291 facility, 9720 borrowing firms, 203 BHCs</td>
<td>172,126</td>
</tr>
<tr>
<td>6</td>
<td>Merge the dataset in step 5 with Compustat to retrieve firm-level accounting information, then match it with the NBER patent database to retrieve patent information by gvkey.</td>
<td>22,201 facility, 3,886 firm, 162 BHCs</td>
<td>75,901</td>
</tr>
<tr>
<td>7</td>
<td>Merge the dataset in step 6 with the CRSP database by permno to retrieve stock returns and market capitalization. Our final sample contains 40,065 unique pairs of bank-firm-year observations for the period of 1986-2006.</td>
<td>3,449 firms, 153 BHCs</td>
<td>40,065</td>
</tr>
</tbody>
</table>
## Appendix B: Variable definitions

### Gravity model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shares</td>
<td>Percentage of deposits a BHC obtains in a given state in a given year</td>
</tr>
<tr>
<td>Distance</td>
<td>Distance between a BHC’s headquarter location and the capital of a given state</td>
</tr>
<tr>
<td>GSP</td>
<td>Gross state product</td>
</tr>
<tr>
<td>CommonBorder</td>
<td>A dummy variable that equal to one if a BHC's home state shares a common land border with a foreign state</td>
</tr>
<tr>
<td>HomeState</td>
<td>A dummy variable that equal to one for all BHC-state pairs where the BHC receives deposits in its home state</td>
</tr>
</tbody>
</table>

### Main regression

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pat</td>
<td>Number of patents filed (and eventually granted) in a given year</td>
</tr>
<tr>
<td>Cite</td>
<td>Number of non-self-citations each patent receives in the subsequent years</td>
</tr>
<tr>
<td>R&amp;D expense</td>
<td>R&amp;D expenditures</td>
</tr>
<tr>
<td>R&amp;D Stock</td>
<td>Obtained by depreciating a firm's R&amp;D expenses over 5 years at a depreciation rate of 20%</td>
</tr>
<tr>
<td>Related patents</td>
<td>Number of patents that are mapped to a firm’s main two-digit SIC industry, i.e., the number of patents that are related to a firm's core business</td>
</tr>
<tr>
<td>Unrelated patent</td>
<td>Number of patents that are unrelated to a firm's core business, computed as total patent counts minus the number of related patents</td>
</tr>
<tr>
<td>Patent_value_avg</td>
<td>Average economic value of patents with patent values computed based on stock market reactions to announcement of patent grants, provided in Kogan et al. (2017).</td>
</tr>
<tr>
<td>Patent_value_sum</td>
<td>Sum of the economic value of all patents with patent values computed based on stock market reactions to announcement of patent grants, provided in Kogan et al. (2017).</td>
</tr>
<tr>
<td>Unknown</td>
<td>Number of patents filed in technology classes that are previously unknown to the firm</td>
</tr>
<tr>
<td>Techproximity</td>
<td>The technological proximity between the patents filed in current year and the existing patent portfolio held by the same firm up to the previous year</td>
</tr>
<tr>
<td>1-HHI</td>
<td>One minus Herfindale Index of bank deposits across states, which measures the actual geographic diversification.</td>
</tr>
<tr>
<td>1-predicted HHI</td>
<td>One minus predicted Herfindale Index of bank deposits across states, which is derived from the gravity-deregulation model. It is the instrument for actual geographic diversification.</td>
</tr>
<tr>
<td>Ln(Sales)</td>
<td>Natural logarithm of total sales</td>
</tr>
<tr>
<td>PPE</td>
<td>Net property, plants and equipment divided by total assets</td>
</tr>
<tr>
<td>CAPXY</td>
<td>Capital expenditures divided by total assets</td>
</tr>
<tr>
<td><strong>Variable</strong></td>
<td><strong>Description</strong></td>
</tr>
<tr>
<td>-------------</td>
<td>----------------</td>
</tr>
<tr>
<td><strong>ROA</strong></td>
<td>Net income divided by total assets</td>
</tr>
<tr>
<td><strong>Leverage</strong></td>
<td>Total book debt divided by total assets</td>
</tr>
<tr>
<td><strong>Tobin Q</strong></td>
<td>(Book value of debt + market value of equity)/ Book value of assets</td>
</tr>
<tr>
<td><strong>H-index</strong></td>
<td>Herfindahl index based on segment annual sales using 2-digit SIC codes</td>
</tr>
<tr>
<td><strong>H-index^2</strong></td>
<td>Square of H-index</td>
</tr>
<tr>
<td><strong>KZIndex</strong></td>
<td>Kaplan-Zingales Index, defined as -1.002<em>cashflow+0.283</em>tobinq+3.319<em>debt-39.368</em>dividend-1.315*cash</td>
</tr>
<tr>
<td><strong>WWIndex</strong></td>
<td>Whited-Wu (2006) index= -0.091<em>Cash flow+0.062</em> Dividend dummy+0.021<em>Long-term debt-0.044</em>Size+0.102<em>Industry sales growth-0.035</em>Sales growth</td>
</tr>
<tr>
<td><strong>Ln(Age)</strong></td>
<td>Natural logarithm of firm age in years, starting from the firm funding year that is defined as the first year it has data available in COMPUSTAT</td>
</tr>
</tbody>
</table>

**Covenant**

<table>
<thead>
<tr>
<th><strong>Covenant</strong></th>
<th><strong>Description</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Financial covenant</strong></td>
<td>Number of financial covenants</td>
</tr>
<tr>
<td><strong>General covenant</strong></td>
<td>Number of general covenants, including dividend restriction, asset sales sweep, assignment restrictions, collateral release, debt issuance sweep, equity issuance sweep, excess cashflow sweep, insurance proceeds sweep, percentage of excess cashflow, percentage of net income, required lenders, and term changes</td>
</tr>
<tr>
<td><strong>Performance covenant</strong></td>
<td>Number of performance covenants, which include maximum debt-to-EBITDA, minimum EBITDA, minimum current ratio, minimum fixed charge coverage, minimum interest coverage, maximum senior debt-to-EBITDA, minimum cash interest coverage, and minimum debt service coverage</td>
</tr>
<tr>
<td><strong>Capital covenant</strong></td>
<td>Number of capital covenants, which include minimum quick ratio, minimum current ratio, maximum debt-to-equity, maximum debt-to-tangible net worth, maximum leverage, maximum senior leverage, minimum net worth, and minimum tangible net worth</td>
</tr>
</tbody>
</table>

As discussed in Murfin (2012), for a covenant that stipulates a minimum value $\gamma$ for the financial ratio $\gamma$ that is normally distributed with standard deviation $\sigma$, tightness can be measured as the probability of a covenant violation:

\[ P = 1 - \Phi \left( \frac{\gamma - \gamma}{\sigma} \right) \],

if a loan package contains multiple covenants, we use the average or max of $P$.

<p>| <strong>B_Rated</strong> | Dummy variable that equals one if the borrower has a B+, B, or B- rating from S&amp;P |
| <strong>Ln(Loan Amount)</strong> | Natural logarithm of the total amount of loans |
| <strong>Ln(Maturity)</strong> | Natural logarithm of time to maturity in months |
| <strong>Performance Pricing</strong> | Dummy variable that equals to one if the loan spread is tied to a firm’s performance |
| <strong>LT2CF</strong> | The ratio of the book value of long-term debt to operating income before depreciation |</p>
<table>
<thead>
<tr>
<th>Term</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ST2CF</td>
<td>The ratio of the book value of short-term debt to operating income before depreciation</td>
</tr>
<tr>
<td>Bank Liquidity</td>
<td>Bank prime rates minus the contemporaneous federal funds rate</td>
</tr>
<tr>
<td>Credit Spread</td>
<td>The spread of Moody’s 10-year BAA bond index over the AAA bond index</td>
</tr>
</tbody>
</table>