Bank Geographic Diversification and Corporate Innovation:

Evidence from the Lending Channel

Abstract

By integrating the staggered interstate bank deregulation into a gravity model, we construct a time-varying bank-specific instrument for geographic diversification, and investigate how geographic expansion affects borrowing firms' innovation via the lending channel. We find that bank geographic diversification boosts both the quantity and quality of borrowing firms' innovation, enables firms to expand innovation scope beyond core business, and enhances the economic value of innovation. Such effects are more pronounced in marginal firms. We identify that relaxing debt covenants and alleviating borrowers' financial constraints are the channels for the documented effects. Beyond impacting the innovation activities of borrowing firms, geographically diversified banks also enhance the innovation capability of borrowing firms via technology spillover from peer firms.

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I. Introduction

How do banking activities affect corporate innovation? Given that the banking industry is one of the most vital sectors that provide "lifeblood" to our economy, and innovation is the engine of economic growth and prosperity (Solow 1957), understanding how banking activities affect corporate innovation is an important research question. Surprisingly there is scarce research in this area. Existing studies examine how state-level bank deregulation affects firm innovation (Chava, Oettl, Subramanian, and Subramanian 2013; Amore, Schneider, and Žaldokas 2013; Cornaggia, Tian, and Wolfe 2015; Hombert and Matray 2016; among others). It is notable that bank deregulation may enhance bank geographic expansion and increase bank competition, both of which may affect corporate innovation. However, these studies do not disentangle these effects, nor are able to "establish whether the increase in innovation stems directly from bank lending to innovative firms" (P837, Amore, Schneider, and Žaldokas, 2013).

In this study, we investigate the causal effect of bank geographic diversification on the innovation activities of their borrowing firms via the lending channel, by employing an improved identification strategy based on the gravity-deregulation approach to construct a time-varying and bank-specific instrumental variable for bank geographic diversification.[1] Consequently, we can disentangle the effect of deregulation on bank geographic expansion from competition, and pin down the changes in innovation activities of borrowing firms stem from geographically diversified banks' lending to those firms.

[1] Other 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), and firm-specific characteristics including CEO overconfidence, stock return liquidity, analyst coverage, and institutional ownership (Galasso and Simcoe 2011; Fang, Tian, and Tice, 2014; He and Tian, 2013; Aghion, Van Reenen, and Zingales 2013).

A major challenge in empirical research that investigates how bank geographic diversification affects corporate innovation is the endogeneity issue. The decision to diversify is endogenous as banks may choose to diversify when the gains outweigh the costs of doing so (Matsusaka 2001). In addition, omitted or unobservable variables that drive bank geographic diversification might also affect corporate innovation (Campa and Kedia 2002). For example, firms in more innovative regions tend to be more innovative due to knowledge spillover and localized social learning (Maskell and Malmberg 1999). Similarly banks may expand operations to more innovative regions to take advantage of the greater business opportunities. Prior studies examine bank deregulation and corporate innovation, typically by using the state-level bank deregulation as an exogenous shock to geographic expansion and competition, and constructing a bank deregulation dummy based on the first year when a state removed barriers to interstate banking (e.g., Kerr and Nanda 2009; Amore, Schneider, and Žaldokas 2013; Chava et al. 2013). However, such an approach is subject to three caveats. First, it ignores the dynamics of state-pair interstate bank deregulation, as each state deregulates at its own pace by either unilaterally opening their state borders to out-of-state banks or by signing bilateral/multilateral agreements with other states to allow the entry of banks in those states. Second, since bank deregulation influences both geographic expansion and competition, using a state level deregulation proxy prevents one from disentangling the effect of bank geographic expansion from competition. Third, a state-level deregulation dummy overlooks potential different exposures to the deregulation shocks among individual banks within the same state.

To overcome the aforementioned endogeneity issue and the caveats in prior studies, we follow Goetz, Laeven, and Levine (2013, 2016) and employ an improved identification strategy in which we integrate the staggered implementation of interstate bank deregulation into a gravity model to project bank asset share in foreign states. Then, we construct a bank-specific and time-varying instrumental variable for bank geographic diversification based on projected asset shares in each state. The exogenous variation of instrument arises from the staggered interstate bank deregulation shocks, pre-determined physical distance between a bank holding company (BHC) headquarters and a foreign state capital, and the market size of home and foreign state. This approach allows us to disentangle the effect of interstate bank deregulation on geographic expansion from competition, and tease out the causal effects of bank geographic diversification on corporate innovation.[2]

To the extent that bank geographic diversification reduces idiosyncratic risk as shown in Goetz, Laeven, and Levine (2016) and Deng and Elyasiani (2008), more geographically diversified banks may be willing to take greater risk, i.e., lending to more risky and innovative firms (Amore, Schneider, and Žaldokas 2013). We argue that bank geographic diversification can spur corporate innovation in the following two ways. First, bank geographic expansion may increase credit supply in the loan market, which may alleviate financial constraints of borrowers, drive down the cost of borrowing and enable borrowers to undertake more innovative and risky projects, thus enhancing 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 (the *Financial Constraints Channel*).

Second, prior literature documents that debt contract terms are crafted contingent on lenders' financial condition. More specifically, Murfin (2012) finds that banks that have experienced recent loan defaults write tighter debt contracts to subsequent borrowers, compared to their peers. As recent defaults update lenders' perception about their own poor screening ability,

[2] Throughout this paper, we use "bank" and "bank holding company (BHC)" interchangeably.

banks may impose tighter loan covenants to compensate for the weaker ex ante screening. Due to their less risky position (Goetz, Levaen, and Levine, 2016), geographically diversified banks might be willing to lend to borrowing firms on more pardoning contract terms (i.e., fewer covenants and/or less stringent covenants). Fewer and less stringent covenants reduce the likelihood of lenders' intervention in the real and financial decisions of borrowing firms, permitting financial and operational flexibility in borrowing firms and spurring firm innovation (the *Debt Covenants Channel*). Echoing such view, Atanassov (2016) argues that firms with less stringent covenants have more flexibility and tolerance to experiment with innovative activities. It is noteworthy that the *Financial Constraints* and *Debt Covenants Channel* are not mutually exclusive so may coexist.

An alternative view is that bank geographic diversification may lead to higher risk as a result of intensified agency problems and a more complex organizational structure that make it more difficult to monitor loans and control risk (Acharya, Hasan, and Saunders 2006; Deng and Elyasiani 2008). More specifically, agency theory suggests that bankers may have incentives to expand geographically for empire building and private benefits such as power, prestige, and compensation, at the cost of declining firm value and increased bank risk (Jensen 1986; Berger and Ofek 1995; Denis, Denis and Sarin 1997). Moreover, bank geographic expansion leads to a more complex organizational structure, which makes it more difficult for the headquarters to monitor its subsidiary banks and manage risk (Brickley, Linck, and Smith 2003; Berger et al. 2005). Existing studies provide empirical evidence supporting such an argument. For example, Demsetz and Strahan (1997) and Chong (1991) find that diversified banks operate with higher leverage and pursue riskier activities, such as lucrative yet risky loans or speculative derivatives trading, which result in higher overall risk. To the extent that bank geographic diversification is associated with higher risk, geographically diversified banks may therefore lend to less risky and innovative firms.

Our results reveal a significant positive causal relationship between bank geographic diversification and innovation output proxied by number of patents and number of non-self-citations per patent. An increase of one standard deviation in bank geographic diversification leads to an increase of 0.37 (0.38) in patent (citation) counts in the subsequent year. We also find that the impact of bank geographic diversification on innovation is statistically significant in marginal firms (i.e., small firms and risky firms). Moreover, 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. Bank geographic diversification also leads to significantly higher economic values of innovation in borrowing firms. Finally, beyond the direct positive effect on borrowing firms' innovation, bank geographic diversification enhances the innovation capability of borrowing firms via technology spillover from peer firms.

The aforesaid theoretical arguments suggest that bank geographic diversification may spur corporate innovation via the *Debt Covenants Channel* and/or the *Financial Constraints Channel*. We document that diversified banks offer loan contracts with fewer covenants and lower covenant intensity, and bank geographic expansion alleviates borrowing firms' financial constraints, lending support to both channels.

Our study is related to a stream of literature that examines bank deregulation and corporate innovation. More specifically, Amore, Schneider, and Žaldokas (2013) document that interstate bank deregulation enhances both the quantity and quality of innovation generated by public manufacturing firms. Cornaggia, Tian, and Wolfe (2015) find that interstate branching 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) document 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) find that innovation in small firms declines following intrastate deregulation, as bank competition impairs their lending relationship; in contrast, innovation in large firms does not decline.

Our paper differs from the aforementioned studies and contributes to the literature in several ways. First, we answer the call in Amore, Schneider, and Žaldokas (2013) by linking banks with borrowing firms using the loan contracts in Dealscan database and providing direct evidence that the increase in corporate innovation stems from geographically diversified banks' lending to innovative firms. Moreover, we employ an improved identification strategy based on the gravity-deregulation approach to construct a time-varying and bank-specific instrumental variable for bank geographic diversification. Doing so enables us to disentangle the effect of interstate bank deregulation on bank geographic expansion from competition, and isolate the direct causal effect of banks' geographic diversification on their borrowers' innovation activities via the lending channel.

Second, we complement the corporate innovation literature by providing insights on how banking activities may affect corporate innovation. We document that banks may affect corporate innovation of borrowing firms through supplying bank credit and altering the strictness of debt covenants, other than intervening the innovation activities of borrowing firms upon covenant violations (Gu, Mao, and Tian 2017). Our study sheds light on how bank diversification affects real economic activities by creating positive externalities on its borrowing firms' investments in innovations. Such insights are of great interests to both corporations and financial market regulators.

Third, we identify debt covenants as a novel channel through which banks affect firm innovation. Covenants in debt contracts are used to mitigate incentive conflicts between shareholders and creditors (Smith and Warner 1979). Nevertheless, prior research has documented that tight loan contracts significantly restrict corporate behavior and financial and operational flexibility (Bradley and Roberts 2015; Dichev and Skinner 2002; Chava and Roberts 2008). Our paper demonstrates that when geographically diversified banks provide more lenient covenants, the borrowing firms enjoy greater financial and operational flexibility, spurring firm innovation. As such, our paper complements the literature on how restrictive debt covenants affect firm's operational flexibility, especially in long term investments in innovative projects.

Lastly, we contribute to the literature by documenting the causal effect of bank geographic diversification on borrowing firms' quantity and quality of innovation, scope of innovation, economic value of innovation. Beyond that, we find that bank geographic diversification enhances the innovation capability of borrowing firms via technology spillover from peer firms. Such analyses portrays 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 variables; Section III discusses the identification strategy and models; Section IV presents empirical results, channels of effects, and robustness checks; Section V concludes.

II. Data and Variables

2.1 Sample selection

We obtain data from various sources. Bank data are obtained from Bank Holding Companies (BHC) database and the bank Call Report. The BHC database provides BHC-specific information, while the Call Report provides bank subsidiary information. We link bank subsidiaries to their parent BHCs that hold at least 50% of the subsidiary's equity by RSSD 9364, following Goetz, Laeven and Levine (2013). Data on stock prices, returns, and market capitalization are obtained from the Center for Research in Security Prices (CRSP) database. We obtain detailed data on patents and citations from the 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 lender-borrower pairs, loan amount, loan spread, maturity, collateral, and covenants, etc.

Our final sample contains 38,486 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.[3] We describe detailed steps documenting how we construct the sample for our analyses in Appendix A.

2.2 Variable construction

2.2.1 Bank geographic diversification

We define bank geographic diversification as the asset dispersion across states based on total assets at bank subsidiary level, which is one minus the Herfindahl-Hirschman index ($1-HHI$), where HHI is computed as the sum of the squared ratios of total assets from all bank subsidiaries in each state to the sum of total assets in all states where a BHC operates. This variable is bounded

[3] We obtain similar results when we winsorize all continuous variables at the top and bottom 1%.

between zero and one, with larger values indicating a higher degree of geographic diversification. The FDIC's Summary of Deposits database provides data on deposits at branch level for each BHC. We also construct alternative geographic diversification measure based on deposit dispersion using branch-level deposits data, as one minus the sum of the squared ratios of total deposits from all bank branches in each state to the sum of total deposits in all states where a BHC operates.

2.2.2 Innovation measures

2.2.2.1 Innovation output

We use patent-based metrics—including patent counts and citation counts—as proxies for firm innovation output following 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 examine 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 (2018) 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 are 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+Pat)*) and the natural logarithm of one plus citation counts (*Ln(1+Cite)*) as the main measures of innovation output.

2.2.2.2 Innovation scope

In addition, we explore each firm's innovation scope by identifying the number of patents that are related or unrelated to the firm's core business. 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 fall 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 (*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 (*Unrelated*). Related patents capture firms' innovation in their core business, while unrelated patents capture their innovation expanding scope to other business lines unrelated to their core business.

2.2.2.3 Economic value of innovation

To investigate the economic 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). 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.

Using stock market reactions to capture patent value is advantageous as the forward looking asset prices 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 use the average economic value of all patents of a firm (*Patent_value_avg*) as well as the sum of economic value of all patents of a firm (*Patent_value_sum*) to proxy for the economic value of innovation.

2.2.3 Control variables

Following Fang, Tian, and Tice (2014), and Mao and Zhang (2018), 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 equipment scaled by total assets *(PPE).* Capital expenditure is measured by capital expenditures divided by total assets *(CAPX).* 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, all 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).[4] Firm age is measured as the logarithm of the number of years since a firm appeared in COMPUSTAT (*Ln(age)*). Detailed variable definitions are summarized in Appendix B.

2.3 Descriptive statistics

[4] *KZIndex* is defined as −1.002×cashflow+0.283×tobinq+3.319×debt−39.368×dividend−1.315×cash.

Our final sample consists of 38,486 firm-BHC-year observations with 11,887 unique firm-year observations. If a firm borrows from multiple banks, the firm-year observation may appear multiple times in the data panel. Panel A of Table 1 presents the summary statistics of the innovation variables along with other firm-specific characteristics of our final sample of unique firm-year observations. An average sample firm has 13.817 patents, with each patent on average receiving 4.326 citations. Among the patents a firm receives, 4.134 (8.814) patents are related (unrelated) to its core business. The average economic value per patent is $4.965 million, and the total economic value for all patents of a firm in a year is $281.4 million.

Panel B of Table 1 presents the summary statistics of bank-specific variables. In our final sample there are 1,056 unique BHC-year observations. The average geographic diversification is 0.095, and an average BHC has 4.238 bank subsidiaries and operates in 1.857 states.

——— Insert Table 1 here ———

III. Identification Strategy and Regression 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 at various paces (Amel 1993). This wave of interstate bank deregulation culminated in the passage of Riegle-Neal Interstate Banking and Branching

Efficiency Act (IBBEA) in 1994, which allowed the nationwide acquisition of banks and opening of de novo branches across state borders, and thereby making nation-wide interstate banking a reality.

Over the evolution of interstate bank deregulation, states removed restrictions on interstate banking in different years and in a staggered manner over time, which generated 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 characteristics such as physical distance and relative market size to project bank asset expansion in foreign states—we use this to further construct a time-varying and BHC-specific instrument variable for geographic diversification. This approach allows us to tease out a causal relationship between bank diversification and borrowing firms' innovation. The instrument variable for bank geographic diversification contains three plausibly exogenous sources of variation including the exogenous interstate bank deregulation shock, the pre-determined distance between bank headquarters and foreign state capital, and the market size of home and foreign state.

We summarize how we carry out this task as follows. First, for each BHC home state we pair it with each of other states in a year, and identify whether the BHC in the home state is legally permitted to enter a foreign state based on the staggered interstate bank deregulation from 1970s to mid-1990s summarized in Amel (1993). 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 those 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, as these two states removed usury ceilings on credit card loans and other types of consumer loans in 1980 and 1981, respectively, shortly before removing bank branching restrictions.

Next, we integrate this staggered bank deregulation into a gravity model that uses geographic distance and market size, etc., to project BHC expansion across state borders, based on which we construct a BHC-specific and time-varying instrumental variable of geographic diversification. In the next section, we detail the gravity-deregulation model based on which we construct the instrumental variable and how we apply it in a two-stage least squares framework to investigate the causal effect of bank geographic diversification on innovation activities of borrowing firms.

3.2 The gravity-deregulation model

In the economics literature, a gravity model is used to construct an 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). Further, pre-determined characteristics such as market size and geographic distance between countries are highly correlated with bilateral trade volume, yet do not influence income, and hence are valid instruments for international trade flow across countries. Building on this idea, Goetz, Laeven, and Levine (2013, 2016) and Levine, Lin and Xie (2016) are among the first in the finance literature to integrate interstate bank deregulation into a gravity model that employs physical distance and market size to project banks' geographic expansion in foreign states.

We make the following improvement based on the gravity-deregulation model proposed in Goetz, Laeven, and Levine (2013, 2016). First, following Frankel and Romer (1999) who find that a common land border shared by two countries plays an important role in determining bilateral trade volume, we include a common land 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. Second, we replace state population with state Gross State Product (GSP) which more accurately reflects the market size and the economy of each state.[5] We also include a home state dummy to account for the possibility that a BHC may expand within its home state.

Our sample includes all possible pairs of BHCs (*b*) and states (*j*) over the period of 1986Q3-2006Q4. Given that the percentage of assets a BHC (*b*) has in a particular state *j* (*Share*) is bounded 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 equation:

$$Share_{bijt} = \beta_1 Distance_{bij} + \beta_2 Ln(GSP\_Home_{it}) + \beta_3 Ln(GSP\_Foreign_{jt}) + \beta_4 CommonBorder_{ij} + \beta_5 HomeState_{ij} + \varepsilon_{bijt}, \quad (1)$$

where the dependent variable $Share_{bijt}$ is the percentage of BHC *b*'s assets in subsidiaries located in state *j* in year *t* and BHC *b* is headquartered in state *i*. $Distance_{bij}$ is the straight-line distance between BHC *b*'s headquarters location in home state *i* and the capital of foreign state *j*. $Ln(GSP\_Home_{it})$ and $Ln(GSP\_Foreign_{jt})$ are the natural logarithm of the Gross State Product (GSP) of BHC *b*'s home state *i* and foreign state *j* in year *t*, respectively. $CommonBorder_{ij}$ is an indicator that equals to one if state *i* and state *j* share a common land border and zero otherwise. $HomeState_{ij}$ is a dummy variable that equals one for a BHC-state pair where BHC *b* allocate assets in its home state *i* (i.e., when $i=j$) and zero otherwise. 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 β_1. Since BHCs are more likely to expand to larger markets and less likely to

[5] Results remain qualitatively similar as we use the exact same gravity-deregulation model in Goetz, Laeven, and Levine (2013, 2016).

expand when their home states have large markets, thus we expect a negative coefficient estimate of β_2 and a positive coefficient estimate of β_3.

Results are presented in Table 2. Average marginal effects are reported in brackets 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 and significant (at 1%), indicating BHCs are more likely to expand to geographically proximate state. The coefficient estimate on home (foreign) *Ln(GSP)* is negative (positive) and significant (at 1%), suggesting that BHCs located in a large-market home state are less likely to expand to a foreign state, and BHCs are more likely to expand to foreign states with large markets.

——— Insert Table 2 here ———

3.3 Two-stage least squares (2SLS) regression

We obtain the predicted value of asset 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 state. We then compute the Herfindahl index of each BHC in a year based on the dispersion of the predicted values of asset shares across all states (*Predicted HHI*). Finally we construct the predicted diversification measure as (*1−Predicted HHI*), which serves as an instrument 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:

$$(1 - HHI)_{bkt} = \alpha_1 + \beta_1(1 - Predicted\ HHI)_{bt} + \gamma_1 X_{kt} + \delta_m + \eta_t + \varepsilon_{bkt}, \qquad (2)$$

$$Innovation_{bk,t+n} = \alpha_2 + \beta_2(1 - HHI)_{bt} + \gamma_2 X_{kt} + \delta_m + \eta_t + \pi_{bkt}\,. \tag{3}$$

The unit of analysis in the 2SLS regressions is at BHC(b)-firm(k)-year(t) level where each firm (k) is linked to one or multiple BHCs (b) through bank loan contracts. $(1-HHI)_{bt}$ is the actual geographic diversification measure based on a BHC (b)'s actual asset dispersion across all states in year t; $(1-Predicted\ HHI)_{bt}$ 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 the subsequent year *t+n.* Given the long duration of innovation projects, we investigate the effect of bank diversification on innovation activities in three subsequent years of t+1, t+2, t+3, and over the three-year period (t+1, t+3). X_{kt} includes a set of firm-specific control variables discussed in Section 2.2.3, including *Ln(Sales)*, *PPE*, *CAPX*, *ROA*, *Leverage*, *Tobin Q*, *H-index*, *H-index^2*, *KZ Index,* and *Ln(Age)*. In addition, δ_m stands for industry-fixed effects based on two-digit SIC codes for industry *m*, and η_t stands for year-fixed effects.

IV. Empirical Results

4.1 Ordinary least square (OLS) results

To gain a sense of the relationship between bank geographic diversification and firm innovation without controlling for the endogeneity issue, we estimate 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 asset dispersion across all states a BHC operates.

Results are reported in Table 3. The coefficient estimates for *(1−HHI)* are negative yet insignificant in all but one model in columns (1) through (4), suggesting that bank diversification generally does not affect patent counts. On the other hand, the coefficient estimates for *(1−HHI)* are negative and significant in all models in columns (5) through (8), suggesting that bank diversification is associated with lower citation counts. Most control variables display signs as expected. Specifically, innovation is higher in larger and older firms, firms with larger capital expenditures and growth opportunity, and firms in more competitive product market. On the other hand, firms with higher asset tangibility and leverage ratios, and more profitable firms innovate less.

Overall, the OLS results suggest that bank geographic diversification is unrelated to innovation quantity, but is negatively related to the quality of innovation. A word of caution is that, bank geographic diversification is endogenous so the coefficient estimates from the OLS estimations could be biased. We employ an instrumental variable approach to address the endogeneity issue in the next section.

——— Insert Table 3 here ———

4.2 Two-stage least squares (2SLS) results

4.2.1 Innovation output: patent and citation counts

To address the endogeneity issues and to 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. Results of the second-stage model explaining the innovation variables (Equation 3) are presented in Panel A of Table 4, where the dependent variables are *Ln(1+Pat)* and *Ln(1+Cite)* in subsequent years t+1, t+2, t+3, and over the (t+1, t+3) period. The coefficient estimates of (*1−HHI*) are positive and significant in all models. The results suggest that bank geographic diversification leads to an increase in both innovation quantity and quality of the borrowing firms in the subsequent three years. The results are also economically significant. For instance, a one standard deviation increase in (*1−HHI*) leads to an increase of 0.37 in patent counts and an increase of 0.38 in the number of non-self-citations per patent in the subsequent year t+1.[6] As with the OLS results in Table 3, the signs on the control variables are mostly consistent with our expectations.

We report the first stage model explaining bank geographic diversification *(1−HHI)* in Panel B of Table 4. The instrument (*1−Predicted HHI*) is positively and significantly (at the 1% level) related to the geographic diversification measure (*1−HHI*) in all models, satisfying the relevance requirement for being a valid 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 152.23 (p-value < 1%), and the weak identification test with Cragg-Donald Wald F statistic is 158.48, 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 (*1−Predicted 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

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[6] The economic magnitudes are computed based on the coefficient estimates on *(1−HHI)* in columns (1) and (5) of Table 4. The standard deviation of (*1− HHI)* for our final sample at BHC-firm-year level is 0.2254, which is a bit different from the standard deviation of 0.188 in the summary statistics for the BHC sample at BHC-year level. Given the coefficient estimate of (*1−HHI*) in column (1) of Table 4 is 1.389, one standard deviation increase of (*1− HHI)* leads to 1.389×0.2254 = 0.313 increase in *Ln(1+Pat)*, and the increase in patent count is exp(0.313) − 1= 0.37. The increase in citation count is 0.38, which is computed in the same way.

in Panel A, the coefficient estimates on (*1−Predicted HHI*) in the reduced form regression remain positive and significant in all models, indicating that bank geographic diversification enhances both the quantity and quality of innovation in borrowing firms.

——— Insert Table 4 here ———

4.2.2 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 of borrowing firms taking greater risk by exploring new innovative projects unrelated to their core business.

To carry out this test, we compute the number of patents that are related (unrelated) to a firm's core business as described in section 2.2.2.2. Similar to other innovation variables, we take the natural logarithm of one plus the number of related patents (*Ln(1+Related)*), and one plus the number of unrelated patents (*Ln(1+Unrelated)*)—in years t+1, t+2, t+3, and over the (t+1, t+3) period—and use them as dependent variables to probe the effect of bank geographic diversification on firm innovation scope. Results are reported in columns (1)–(4), and columns (5)–(8) of Table 5, respectively. Results in columns (5)–(8) show that bank geographic diversification has a significant positive effect on the number of unrelated patents in each of the subsequent three years as well as over the three-year period. The effect is also economically significant. Based on the point estimates in column (5), a one standard deviation increase in (*1−HHI*) leads to an increase of 0.265 in unrelated patent counts in the subsequent year t+1.[7] In contrast, geographic

[7] The economic magnitudes are computed based on the coefficient estimates on *(1−HHI)* in column (5) of Table 6. The standard deviation of (*1− HHI)* for our final sample at BHC-firm-year level is 0.2254. Given the coefficient

diversification has little significant effect on the number of related patents in any of the subsequent three years (see columns (1)–(4)). The results indicate that bank diversification enables firms to expand their innovation scope to explore innovation activities beyond their core business.

——— Insert Table 5 here ———

4.2.3 Economic value of innovation

While patent citations reveal the scientific value of innovation, they do not offer much information on the economic value a patent may generate for a firm. Kogan et al. (2017) compute the economic value of each patent based on stock market reaction to announcements of patent grants. To shed light on this, we obtain patent economic value data from Professor Noah Stoffman's website.[8] Since many firms hold multiple patents in a given year, we use both the average economic value of each patent (*Patent_value_avg*) and the sum of economic value of all patents (*Patent_value_sum*) for each firm. We then examine how bank diversification affects the economic values of patents produced by their borrowing firms. The dependent variables are the natural logarithm of one plus *Patent_value_avg (Ln(1+Patent_value_avg)*) and *Patent_value_sum* (*Ln(1+Patent_value_sum)*)—in years t+1, t+2, t+3, and over the (t+1, t+3) period—with results reported in columns (1)–(4), and (5)–(8) of Table 7, respectively.

We find that bank geographic expansion not only leads to significantly higher total economic value for all patents in all years but year t+3, but also higher average economic value per patent in each of the three subsequent years t+1, t+2, t+3, as well as over the (t+1, t+3) period. By exploring

estimate of (*1−HHI)* in column (5) of Table 6 is 1.043, one standard deviation increase of (*1− HHI)* leads to 1.043×0.2254 = 0.2351 increase in *Ln(1+Unrelated)*, and the increase in unrelated patent count is exp(0.2351) − 1= 0.265.

[8] We thank Professor Stoffman for graciously making the patent data publicly available at https://iu.app.box.com/v/patents.

innovation beyond firms' main business, firms realize greater economic value of innovation, as innovative activities unrelated to their core business enable the firms to expand their business boundary and better explore opportunities in a competitive business environment.

In sum, bank geographic diversification boosts borrowing firms' 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 enhances economic value of innovation.

——— Insert Table 6 here ———

4.3 Effects on marginal firms

As banks expand geographically to penetrate new states, they are more likely to go after marginal firms, e.g., those small firms and risky firms, due to local bank competition. Marginal firms are small and risky, have little access to the capital market, and hence are more dependent on bank financing. Such marginal firms could benefit the most from geographic expansion of out-of-state banks via the ample credit supply. In addition, Amore, Schneider, and Žaldokas (2013) argue that bank geographic diversification reduces bank credit risk, which enables them to make loans to riskier borrowers. Thus we expect the impact of bank geographic diversification on corporate innovation to be more pronounced in small and risky firms. To test this conjecture, we divide the sample firms into two groups, *Large firms* vs. *Small firms,* where large firms are those with firm size (*Size*) greater than the sample median and the rest are categorized as small firms. We re-estimate equation (2) and (3) separately for these two subsamples, results are reported in Table 7 Panel A and B for large and small firms respectively. We observe that the impact of bank geographic diversification on innovation is positive and significant for small firms (see Panel A), while that for large firms is statistically insignificant (see Panel B).

We also divide the sample into two subgroups, *High risk firms* vs. *Low risk firms,* where high risk firms are those with standard deviation of stock returns greater than the sample median and the rest are categorized as low risk firms. We re-estimate equation (2) and (3) separately for these two subgroups. Results show that the impact of bank geographic diversification on innovation is positive and significant for high risk firms (see Panel C of Table 7), while that for low risk firms is statistically insignificant (see Panel D of Table 7).

In sum, we find that bank geographic diversification enhances innovation but only in marginal firms—those small and risky firms. Bank geographic expansion allows marginal firms that are financially constrained to take advantage of the credit supply from out-of-state banks and invest in innovative projects.

——— Insert Table 7 here ———

4.4. 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.

4.4.1 Debt covenants channel

Jensen and Meckling (1976) suggest that the risk-shifting incentive of equity-holders may prompt creditors to restrict investments via 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 impacts of binding covenants on borrowers can be material and substantial, which range from constrained access to otherwise committed credit facilities (Sufi 2009) to heightened creditor influence over the financial and investment decisions of the firm (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, generally contracts do not contain covenants with explicit restrictions on firms' innovation activities. Nevertheless, the majority of debt covenants are tied to a firm's Debt/EBITDA ratio and net worth, and innovation inputs such as R&D expenditures are expensed immediately, thereby reducing 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 long-term and innovative investments to less risky and short-term projects that may generate more stable cash flows, which naturally curtails innovation.

Prior studies document that debt contract terms are related to banks' financial condition. For example, Murfin (2012) finds that banks that have experienced loan defaults write tighter debt contracts, compared to their peers; further, this pattern holds even when defaulting borrowers are in different industries and different geographic regions than the current borrowers. The evidence suggests that recent defaults inform a lender about its own screening ability, and hence affecting 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 covenants and less stringent covenants). 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, stimulating innovation activities. 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.

To test the above conjecture, we construct multiple measures of covenants, including number of general covenants (*General_Cov*), number of financial covenants (*Financial_Cov*), number of performance covenants (*Performance_Cov)* [9], number of capital covenants (*Capital_Cov*)[10]. See Appendix B for detailed definitions of the covenant variables. Additionally, we follow Bradley and Roberts (2015) to construct covenant intensity index (*Intensity_Cov*), which covers six categories of covenants including secured debt, dividend restrictions, more than two restricted financial ratios, asset sweep, debt sweep, and equity sweep covenants. Likewise, covenant intensity proxies for the degree of restrictions to managers posed by loan contracts, with a higher value indicating greater restrictions to firm management.

To investigate the debt covenant channel, we assess how bank geographic diversification affects the covenant terms in their loan contracts in a 2SLS regression framework. Following Wang and Xia (2014), we include a set of control variables including S&P credit ratings (*A_Rated* and *B_Rated*), loan size, maturity, performance pricing, long term debt to operating income ratio, short term debt to operating income ratio, bank liquidity, and credit spread in the model of covenants. Results are reported in Table 8.

We find that the coefficient estimates for geographic diversification are all negative and significant except for those in column (4) with respect to capital covenants. This indicates that geographically diversified banks offer loans with significantly fewer financial and general

[9] 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.
[10] 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.

covenants, fewer performance covenants and lower covenant intensity. However, we find no significant effect on capital covenants.

The differential effect on performance covenants and capital covenants is interesting. Christensen and Nikolaev (2012) argue that performance covenants (e.g., debt-to-EBITDA, interest coverage) serve as trip wires that curb agency problems by allocating control rights to lenders in states where creditors' claims are at risk, and are tied to the outcome of the investments, which likely dampen borrowers' incentives to take excessive risk. Diversified banks offer loans with fewer performance covenants, which may allow borrowers to take risks in innovative projects whose risk would otherwise be too large. In contrast, capital covenants (e.g., leverage, net worth) alleviate agency problems by aligning the interest of creditors and shareholders (Christensen and Nikolaev 2012). While capital covenants restrict the amount of resources a borrower can invest, they do not necessarily limit the riskiness of the investment. As such, diversified banks need not relax capital covenants in order to encourage borrowers' risk-taking incentive.

Overall our results lend support to the debt covenants 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 spurring innovation activities.

——— Insert Table 8 here ———

4.4.2 Financial constraints channel

Bank geographic expansion enables local firms to obtain bank loans from out-of-state banks. The increase in bank credit supply alleviates the financial constraints of borrowing firms. As a result, firms can deploy the much-needed bank credit to launch innovative projects that may boost corporate innovation. To test this channel effect, we employ three measures of financial constraints, *KZIndex*, *WWIndex*, and *SAIndex*, as dependent variables, and regress each on bank geographic diversification, along with *Ln(Sales)*, *PPE*, *CAPX*, and *ROA* as control variables. *KZIndex* is the Kaplan and Zingales (1997) index as defined above, *WWIndex* is the Whited-Wu (2006) index,[11] and *SAIndex* is the Size-Age index in Hadlock and Pierce (2010).[12]

Empirical results are reported in Table 9. We observe a negative and significant (at the 1% level) coefficient estimate on the geographic diversification measure in all models explaining three measures of financial constraints, suggesting that bank diversification alleviates borrowers' financial constraints which in turn boosts their innovation.

——— Insert Table 9 here ———

4.5 Additional analysis: technology spillover

Above we document that bank geographic diversification spurs borrowing firms' innovation through lessening restrictive debt covenants and alleviating borrowers' financial constraints. In this section, we explore whether bank geographic expansion affects the innovation capability of borrowing firms via technology spillover from peer firms.

Brandenburger and Nalebuff (1996) epitomize the concept of "coopetition" in technology competition — firms learn from one another and may collaborate as they compete in product market, leading to "technology spillover". Technology is often built upon others' and technology

[11] *WWIndex* is defined as −0.091×Cash flow+0.062× Dividend dummy+0.021×Long-term debt − 0.044×Size +0.102×Industry sales growth− 0.035×Sales growth.
[12] *SAIndex* is calculated as: −0.737× Size + 0.043× Size^2 − 0.040×Age. Size is log of book assets, and age is the number of years the firm has been on COMPUSTAT with a non-missing stock price. When calculating this index, if book assets is greater than $4.5 billion and age is larger than 37 years, size is replaced with log($4.5 billion) and age is replaced with 37 years.

spillovers improve R&D productivity (Griliches 1979). Technology spillover could be generated via learning and emulation, upstream and downstream linkages in the supply chain, and mobility of skilled workers. The extent of taking advantage of technology spillover may however be limited by financial constraints. Qiu and Wan (2015) show that firms hold more cash when facing greater opportunities of technology spillovers to avoid the inability to raise sufficient funds to take advantage of diffused technology. Enhanced credit supply from geographically diversified banks will consequently facilitate borrowing firms to better take advantage of technology spillover from peer firms.

To test this conjecture, we follow Jaffe (1986), Qiu and Wan (2015), and Tseng (2018), and use technology-weighted sum of peer firms' R&D stock to measure technology spillover (*Spillover*), which is constructed as follows:

$$Spillover_{it} = \sum_{j \neq i} Tech_{ijt} \times RDStock_{jt} \,, \tag{4}$$

where $RDStock_{jt}$ is R&D stock of firm *j* at time *t*. Following Qiu and Wan (2015) and Tseng (2018), we compute $RDStock_{jt}$ using a perpetual inventory method in that

$$RDStock_{jt} = RD_{jt} + (1-\delta)\ RDStock_{jt-1}, \tag{5}$$

with RD_{jt} being the R&D expenditures of firm *j* and δ being the depreciation rate that takes the value of 0.15.

To measure $Tech_{ijt}$ we use the cosine similarity developed in Jaffe (1986) which measures the similarity between a firm's patent portfolio and that of each of other firms. The idea is that a firm is more likely to benefit from the R&D stock of other firms that are technologically similar to it. More specifically, a firm's patent portfolio is converted to a vector $T_i = (T_{i1}, T_{i2}, ..., T_{i428})$, where T_{ι} is the percentage of patents of a firm among the overall patents in a technology class ι There are 428 different three-digit technology classes. The similarity of two firms' patent portfolio can be measured as the angle between the two vectors in an N-dimensional space. Assuming technology classes are independent of each other (Jaffe 1986), we calculate the cosine similarity for each firm-pair in a given year as follows:

$$Tech_{ij} = \frac{T_i T_j'}{\sqrt{T_i T_i'} \times \sqrt{T_j T_j'}} . \tag{6}$$

We then use $Tech_{ij}$ as the weight to calculate the weighted sum of R&D stock of all other firms in the industry, which we employ as the technology spillover measure.

The Jaffe (1986) cosine similarity measure assumes that technology spillover only occur in patents within the same technology class but not across technology classes. To address the concern that technology classes may be correlated and technology spillover may occur across technology classes, we follow Bloom et al. (2013), Qiu and Wan (2015), and Tseng (2018) to construct the Mahalanobis distance metric of Jaffe's measure − $Tech\_Mah_{ij}$ as follows:

$$Tech\_Mah_{ij} = \frac{T_i \Omega T_j'}{\sqrt{T_i T_i'} \times \sqrt{T_j T_j'}} , \tag{7}$$

where Ω is a 428×428 Mahalanobis matrix summarizing the correlation of technology classes among firms. For the sake of brevity, we report the calculation of **Ω** in appendix C. Technology spillover based on Mahalanobis matrix for firm *i* in year *t* is calculated as:

$$Spillover\_Mah_{it} = \sum_{j \neq i} Tech\_Mah_{ijt} \times RDStock_{jt} . \tag{8}$$

We estimate the 2SLS regressions using *Spillover* and *Spillover_Mah* as the dependent variable, results are presented in Table 10. We find that bank geographic diversification leads to greater technology spillover measured by both Jaffe (1986) spillover (*Spillover*) and Mahalanobis metric spillover (*Spillover_Mah*), and the results are statistically significant (at the 1% level) in all models. The finding confirms our conjecture that bank geographic diversification not only boosts corporate innovation in borrowing firms, but also enables borrowing firms to better take advantage of technology spillover from peer firms.

——— Insert Table 10 here ———

4.6 Robustness checks

4.6.1 Placebo test

It is possible that the increase in corporate innovation that we document might be the result of a predetermined trend that coincides with interstate bank deregulation. If this is the case, we should observe the co-movement of corporate innovation and bank geographic expansion regardless of the exact timing of interstate bank deregulation. 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.[13] That is, we falsely assume a BHC can legally enter a foreign state at a random year 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) and (4) in a 2SLS framework.

[13] 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.

The 2nd stage results explaining patent counts and citation counts are presented in Table 11. We find that none of the coefficient estimates on bank geographic diversification (*1−HHI*) is significant, suggesting no significant impact of geographic diversification resulted from the falsely assumed bank deregulation years on innovation. Therefore, we find additional support that our documented effects on corporate innovation are driven by bank geographic expansion due to the interstate bank deregulation, rather than some time trend.

——— Insert Table 11 here ———

4.6.2 Alternative model of constructing the instrumental variable

To check the robustness of our results, we employ the same model specification as that in Goetz, Laeven, and Levine (2013, 2016) to construct the instrumental variable, which is as follows:

$$Share_{bijt} = \alpha Ln(Distance_{bij}) + \beta Ln(Pop_{it} / Pop_{jt}) + \varepsilon_{bijt}, \tag{9}$$

where $Share_{bijt}$ is the percentage of BHC *b*'s assets in all subsidiaries in state *j* in year *t* and BHC *b* is headquartered in state *i*. $Distance_{bij}$ is the straight-line distance between BHC *b*'s headquarter location in home state *i* and the capital of foreign state *j*. $Ln(Pop_{it}/Pop_{jt})$ is the natural logarithm of the ratio of population in BHC *b*'s home state *i* and that in a foreign state *j* in year *t*. We use the predicted shares from Equation (5) to calculate *Predicted HHI*, and then use *(1−Predicted HHI)* as an instrument for the actual level of geographic diversification (*1−HHI*). We estimate models (3) and (4) simultaneously using a 2SLS technique. The 2nd stage results from the 2SLS regressions (reported in Panel A of Table 12) show that the effect of bank geographic diversification on both the quantity and quality of innovation remain positive and significant at the 5% level or better.

4.6.3 Alternative measure of geographic diversification

In the results above, we use asset dispersion across state based on total assets at bank subsidiary level as a proxy for bank geographic diversification. Alternatively we employ data from the FDIC's Summary of Deposits to compute deposit dispersion across state based on total deposits at branch level as an alternative measure of bank geographic diversification. Results are reported in Panel B of Table 12. The coefficient estimate on ($1-HHI$) is positive and significant in all but one model, confirming the robustness of our results using asset dispersion.

4.6.4 Subsample containing lead banks only

Prior studies on bank loan contracting mostly focus on the lead banks of syndicated loans (e.g., Graham, Li, and Qiu 2008; Deng, Willis, and Xu 2014; Campello and Gao 2017). In our main analyses, we retain both lead banks and participant banks in a syndicate as both types of bank provide funding and hence may enhance the innovation activities of borrowing firms.[14] 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 to those reported before despite a near halving of the sample size.

4.6.5 *Estimating the 1st and 2nd stage models separately*

Since the unit of analysis is a firm-bank-year observation, when a firm borrows from multiple lenders, the firm-year observation appears multiple times in the data panel, hence the regressions tend to over-weigh the firms that borrows from multiple lenders in a year. To mitigate this issue, we repeat the 2SLS regressions using firm-year observations. To do so we estimate the first- and second-stage models separately. We estimate the first-stage model of bank

[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.

geographic diversification (Equation (2)) to obtain ($1-$*Predicted HHI*), then calculate the average of ($1-$*Predicted HHI)* of all lenders from which a firm borrows bank loans. As a result, our sample collapses to firm-year observations with the bank geographic diversification variable being the average across the multiple lenders of a borrower in a given year. Finally we estimate the second-stage model explaining the innovation variables (Equation (3)), where the average of ($1-$*Predicted HHI*) is the independent variable. The results remain positive and significant, as shown in Panel D of Table 12.

——— Insert Table 12 here ———

V. Conclusion

In this paper, we examine the causal relationship between bank geographic diversification and corporate innovation using an improved identification strategy following Goetz, Laeven, and Levine (2013, 2016). 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 a time-varying and BHC-specific instrumental variable for bank geographic diversification. This approach allows us to disentangle the effect of deregulation on bank geographic expansion from competition. Furthermore, by linking borrowing firms with lending banks via loan contracts, our study enables us to pin down the effect on innovation that is directly attributable to geographically diversified banks' lending to these firms. Therefore, our study answers the call in Amore, Schneider, and Žaldokas (2013) and sheds light on the causal effect of banks' geographic diversification on their borrowers' innovation activities via the lending channel.

Empirical results show that bank geographic diversification boosts both the quantity and quality of borrowing firms' innovation, enables firms to expand innovation scope by developing lines of business that are unrelated to their core business, and enhances economic value of innovation. Further analyses reveal that bank geographic diversification enhances innovation only in marginal firms (i.e., small firms and risky firms). Furthermore, we explore potential channels via which bank diversification affects borrowing firms' innovation. We find evidence consistent with both the debt covenant channel and financial constraints channel. Lastly, we document that beyond impacting borrowing firms' innovation activities, geographically diversified banks also enhance the innovation capability of borrowing firms via technology spillover from peer firms.

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Table 1: Summary Statistics

This table provides summary statistics for our sample during the period between 1986 and 2006. Panel A presents firm-specific variables, with observations uniquely identified by firm-year. Panel B presents 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 3,449 firms borrowing from 153 unique BHCs.

Panel A. Firm-specific variables								
Variable	N	Mean	Sd	Min	P25	P50	P75	Max
Pat_{t+1}	11,887	13.817	56.887	0.000	0.000	0.000	2.000	475.000
$Cite_{t+1}$	11,887	4.326	9.171	0.000	0.000	0.000	4.258	44.800
$Related_{t+1}$	11,887	4.134	17.900	0.000	0.000	0.000	0.140	148.000
$Unrelated_{t+1}$	11,887	8.814	36.000	0.000	0.000	0.000	1.161	294.400
Patent_value_avg ($million)	11,887	4.965	20.490	0.000	0.000	0.000	1.463	315.700
Patent_value_sum($million)	11,887	281.400	1965.000	0.000	0.000	0.000	3.417	34708.000
Ln(Sales)	11,876	6.496	1.948	2.807	5.078	6.447	7.848	11.270
PPE	11,887	0.291	0.214	0.004	0.125	0.239	0.412	0.882
CAPX	11,887	0.061	0.056	0.000	0.025	0.044	0.076	0.289
ROA	11,887	0.015	0.121	-0.469	0.001	0.038	0.073	0.244
Leverage	11,854	0.284	0.199	0.000	0.135	0.268	0.397	0.930
Tobin Q	11,886	1.762	1.088	0.651	1.105	1.417	1.995	6.676
H-index	11,887	0.066	0.061	0.008	0.036	0.047	0.074	0.391
H-index^2	11,887	0.008	0.021	0.000	0.001	0.002	0.005	0.153
Ln(Age)	11,887	2.717	0.919	0.693	1.946	2.773	3.584	4.043
KZ Index	11,470	4.142	14.670	-29.790	0.234	2.022	4.873	119.700
WW index	11,612	-0.321	0.110	-0.590	-0.401	-0.318	-0.238	-0.116
SA index	11,887	-3.631	0.887	-5.347	-4.391	-3.477	-2.985	-2.034
Panel B. BHC-specific variables	N	Mean	Sd	Min	P25	P50	P75	Max
1-HHI	1,056	0.095	0.188	0.000	0.000	0	0.0843	0.846
Number of Subsidiaries	1,056	4.238	7.050	1.000	1.000	2.000	4.000	77.000
Number of States	1,056	1.857	1.620	1.000	1.000	1.000	2.000	15.000

Table 2. Gravity-Deregulation Model

This table reports the results of fractional logit regression based on the gravity-deregulation model to project bank asset share in a foreign state:

$$Share_{bijt} = \beta_1 Distance_{bij} + \beta_2 Ln\left(GSP\_home_{it}\right) + \beta_3 Ln\left(GSP\_foreign_{jt}\right) + \beta_4 CommonBorder_{ij} + \beta_5 HomeState_{it} + \varepsilon_{bijt}$$

where the dependent variable $Share_{bijt}$ is the percentage of BHC *b's* assets in state *j* in a quarter *t* and BHC *b* is headquartered in state *i*. $Distance_{bij}$ is the straight-line distance between BHC *b*'s headquarter in home state *i* and the capital of foreign state *j*. GSP_home_{it} is Gross State Product (GSP) of a BHC's home state *i* in quarter *t*, while $GSP\_foreign_{jt}$ is the GSP of a foreign state *j* to which the BHC *b* allocates its assets in quarter *t*. $CommonBorder_{ij}$ is an indicator variable that equals one if state *i* and state *j* share a common land border. $Homestate_i$ is a dummy variable that equals to one if a BHC allocate assets in the home state *i*. Standard errors are clustered at state-year level. Marginal effects are reported in the brackets, and t-values are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

		Share	
	(1)	(2)	(3)
Distance	-1.1623***	-1.4041***	-0.1387***
	[-0.0221]	[-0.0261]	[-0.0003]
	(-42.677)	(-26.097)	(-6.898)
Ln(GSP_home)		-0.5020***	-0.6284***
		[-0.0093]	[-0.0014]
		(-13.132)	(-24.928)
Ln(GSP_foreign)		0.5564***	0.1132***
		[0.0103]	[0.0002]
		(13.895)	(4.086)
CommonBorder			1.7401***
			[0.0041]
			(21.259)
HomeState			9.7335***
			[0.0229]
			(70.323)
N	1,331,120	1,331,120	1,331,120

Table 3. Bank Geographic Diversification and Corporate Innovation Output ─ OLS Regression

This table presents OLS results. The dependent variables are patent and citation counts. Patent count is measured by *Ln(1+Pat)*, which is the natural logarithm of one plus the total number of patents filed (and eventually granted). Citation count is measured by *Ln(1+Cite)*, which is the natural logarithm of one plus the total number of non-self-citations received per patent. The independent variable of interest is *(1−HHI)*, which is one minus Herfindahl index of lending bank's assets across states. We use heteroscedasticity-robust standard errors and report t-values in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Ln(1+Pat)				*Ln(1+Cite)*			
	t+1	*t+2*	*t+3*	*(t+1,t+3)*	*t+1*	*t+2*	*t+3*	*(t+1,t+3)*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1−HHI	**-0.037**	**-0.044***	**-0.042**	**-0.135**	**-0.039***	**-0.049****	**-0.045****	**-0.051***
	(-1.562)	**(-1.919)**	**(-1.938)**	**(-1.890)**	**(-1.908)**	**(-2.544)**	**(-2.539)**	**(-1.908)**
Ln(Sales)	0.336***	0.301***	0.265***	1.004***	0.173***	0.148***	0.136***	0.220***
	(77.602)	(72.106)	(67.258)	(75.406)	(52.032)	(47.650)	(47.424)	(51.478)
PPE	-0.335***	-0.279***	-0.229***	-1.036***	-0.297***	-0.205***	-0.208***	-0.408***
	(-6.848)	(-5.948)	(-5.287)	(-6.500)	(-7.382)	(-5.289)	(-5.932)	(-7.568)
CAPX	1.593***	1.426***	1.209***	4.869***	0.926***	1.130***	1.033***	1.490***
	(10.724)	(10.035)	(9.110)	(9.606)	(7.246)	(8.946)	(8.972)	(8.327)
ROA	-0.193***	-0.187***	-0.126***	-0.994***	-0.035	-0.059**	-0.063***	-0.014
	(-5.353)	(-5.494)	(-4.222)	(-4.835)	(-1.255)	(-2.321)	(-2.759)	(-0.366)
Leverage	-0.345***	-0.350***	-0.289***	-1.103***	-0.256***	-0.246***	-0.224***	-0.405***
	(-10.555)	(-10.908)	(-10.090)	(-9.402)	(-9.522)	(-9.372)	(-9.392)	(-10.797)
Tobin Q	0.043**	0.041**	0.036**	0.127*	0.026*	0.022*	0.017*	0.033*
	(2.036)	(2.020)	(1.992)	(1.789)	(1.921)	(1.942)	(1.958)	(1.895)
H-index	0.911***	0.856***	0.893***	4.710***	1.934***	1.784***	1.672***	2.756***
	(3.384)	(3.248)	(3.505)	(3.805)	(6.028)	(5.916)	(5.214)	(6.299)
H-index^2	-1.343***	-1.721***	-2.262***	-8.837***	-3.525***	-3.284***	-3.686***	-5.264***
	(-2.718)	(-3.609)	(-4.934)	(-3.399)	(-5.392)	(-5.537)	(-5.601)	(-5.920)
KZ Index	0.000**	0.000**	0.000***	0.001**	0.000***	0.000*	0.000*	0.000**
	(2.353)	(2.314)	(2.719)	(2.437)	(2.818)	(1.930)	(1.926)	(2.142)
Ln(Age)	0.104***	0.088***	0.072***	0.247***	0.033***	0.041***	0.031***	0.037***
	(12.615)	(10.905)	(9.514)	(9.403)	(4.622)	(6.197)	(5.031)	(3.973)
Industry fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	38,486	38,486	38,486	38,486	38,486	38,486	38,486	38,486

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+Pat)* is the natural logarithm of one plus the total number of patents filed (and eventually granted). *Ln(1+Cite)* is the natural logarithm of one plus the total number of non-self-citations received per patent. The independent variable of interest is bank geographic diversification (*1−HHI*). Panel B reports the results of the first-stage model of bank geographic diversification, with the instrument variable being one minus the Predicted value o*f HHI* based on the gravity-deregulation model. Panel C reports the results of the second-stage model explaining innovation based on reduced form regressions. All other variables are defined in Appendix B. We use heteroscedasticity-robust standard errors and report t-values in the parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: 2SLS second stage results

	Ln(1+Pat)				*Ln(1+Cite)*			
	t+1	*t+2*	*t+3*	*(t+1,t+3)*	*t+1*	*t+2*	*t+3*	*(t+1,t+3)*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1−HHI	**1.389*****	**1.176*****	**0.710****	**4.030*****	**1.429*****	**0.935*****	**0.469***	**1.644*****
	(3.629)	**(3.238)**	**(2.156)**	**(3.013)**	**(4.573)**	**(3.381)**	**(1.922)**	**(4.143)**
Ln(Sales)	0.342***	0.307***	0.269***	1.188***	0.179***	0.152***	0.138***	0.228***
	(70.638)	(66.109)	(62.463)	(64.717)	(47.034)	(43.998)	(44.679)	(46.866)
PPE	-0.329***	-0.274***	-0.226***	-1.140***	-0.291***	-0.201***	-0.206***	-0.401***
	(-6.476)	(-5.673)	(-5.162)	(-6.273)	(-6.823)	(-5.031)	(-5.832)	(-7.126)
CAPX	1.593***	1.426***	1.209***	6.073***	0.926***	1.130***	1.033***	1.489***
	(10.288)	(9.708)	(8.986)	(10.120)	(6.859)	(8.716)	(8.927)	(8.029)
ROA	-0.199***	-0.192***	-0.129***	-1.128***	-0.042	-0.063**	-0.065***	-0.021
	(-5.284)	(-5.448)	(-4.233)	(-4.733)	(-1.360)	(-2.373)	(-2.804)	(-0.539)
Leverage	-0.330***	-0.338***	-0.281***	-1.098***	-0.242***	-0.236***	-0.218***	-0.388***
	(-9.844)	(-10.325)	(-9.716)	(-8.705)	(-8.613)	(-8.796)	(-9.090)	(-10.065)
Tobin Q	0.045**	0.042**	0.037**	0.147*	0.027**	0.023**	0.018**	0.035**
	(2.088)	(2.069)	(2.030)	(1.843)	(2.001)	(2.008)	(2.006)	(1.967)
H-index	0.905***	0.852***	0.890***	7.195***	1.928***	1.780***	1.670***	2.750***
	(3.130)	(3.062)	(3.416)	(4.840)	(5.664)	(5.732)	(5.172)	(6.043)
H-index^2	-1.430***	-1.795***	-2.308***	-13.906***	-3.614***	-3.344***	-3.717***	-5.367***
	(-2.679)	(-3.552)	(-4.908)	(-4.506)	(-5.252)	(-5.501)	(-5.618)	(-5.846)
KZ Index	0.000**	0.000**	0.000***	0.001**	0.000**	0.000*	0.000*	0.000*
	(2.158)	(2.197)	(2.691)	(2.141)	(2.520)	(1.807)	(1.894)	(1.956)

Ln(Age)	0.109***	0.091***	0.075***	0.266***	0.037***	0.044***	0.032***	0.041***
	(12.649)	(11.028)	(9.703)	(8.939)	(4.937)	(6.426)	(5.212)	(4.310)
Industry fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Kleibergen-Paap rk LM statistic	152.23	152.23	152.23	152.23	152.23	152.23	152.23	152.23
Cragg-Donald Wald F statistic	158.48	158.48	158.48	158.48	158.48	158.48	158.48	158.48
N	38,486	38,486	38,486	38,486	38,486	38,486	38,486	38,486

Panel B: 2SLS first stage results

	1−HHI				*1−HHI*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1−Predicted HHI	**0.453*****	**0.453***	**0.453***	**0.453***	**0.453***	**0.453***	**0.453***	**0.453***
	(12.503)	**(12.503)**	**(12.503)**	**(12.503)**	**(12.503)**	**(12.503)**	**(12.503)**	**(12.503)**
Control Variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Industry fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	38,486	38,486	38,486	38,486	38,486	38,486	38,486	38,486

Panel C: Reduced form results

	Ln(1+Pat)				*Ln(1+Cite)*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1− Predicted HHI	**0.629***	**0.532***	**0.321**	**1.765***	**0.647***	**0.424***	**0.212***	**0.744***
	(3.796)	**(3.352)**	**(2.186)**	**(3.126)**	**(4.905)**	**(3.508)**	**(1.940)**	**(4.385)**
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	38,486	38,486	38,486	38,486	38,486	38,486	38,486	38,486

Table 5: Bank Geographic Diversification and Innovation Focus – 2SLS regressions

This table reports the second-stage of the 2SLS regression results showing how bank geographic diversification affects borrowing firms' innovation focus. *Ln(1+Related)* 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; *Ln(1+ Unrelated)* 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. Independent variable of interest is bank geographic diversification (*1−HHI*), which is instrumented using one minus the Predicted value o*f HHI* from the gravity-deregulation model. All other variables are defined in Appendix B. We use heteroscedasticity-robust standard errors and report t-values in the parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Ln (1+Related)				*Ln (1+Unrelated)*			
	t+1	*t+2*	*t+3*	*(t+1, t+3)*	*t+1*	*t+2*	*t+3*	*(t+1, t+3)*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1−HHI	**0.188**	**0.217**	**0.106**	**0.276**	**1.043*****	**0.896****	**0.637***	**0.966****
	(0.601)	**(0.721)**	**(0.381)**	**(0.714)**	**(2.611)**	**(2.338)**	**(1.799)**	**(2.017)**
Ln(Sales)	0.275***	0.251***	0.221***	0.314***	0.374***	0.345***	0.306***	0.404***
	(63.444)	(59.634)	(54.989)	(58.317)	(69.914)	(65.747)	(60.521)	(62.194)
PPE	-0.274***	-0.260***	-0.224***	-0.309***	-0.397***	-0.357***	-0.325***	-0.402***
	(-6.565)	(-6.428)	(-6.020)	(-6.065)	(-7.739)	(-7.195)	(-7.109)	(-6.523)
CAPX	1.644***	1.532***	1.345***	1.827***	1.755***	1.647***	1.426***	1.912***
	(12.409)	(11.935)	(11.077)	(11.107)	(11.650)	(11.259)	(10.347)	(10.352)
ROA	-0.178***	-0.165***	-0.114***	-0.144***	-0.255***	-0.248***	-0.175***	-0.219***
	(-5.871)	(-5.809)	(-4.452)	(-3.973)	(-6.894)	(-7.082)	(-5.659)	(-5.141)
Leverage	-0.228***	-0.246***	-0.204***	-0.306***	-0.315***	-0.316***	-0.252***	-0.364***
	(-9.168)	(-9.957)	(-9.261)	(-9.656)	(-9.420)	(-9.819)	(-8.764)	(-9.117)
Tobin Q	0.041**	0.038**	0.035**	0.050**	0.041**	0.040**	0.036**	0.050**
	(2.050)	(2.030)	(2.013)	(2.024)	(2.140)	(2.112)	(2.089)	(2.087)
H-index	0.489**	1.070***	1.488***	1.564***	0.714**	0.828***	0.875***	0.872**
	(2.564)	(5.495)	(7.139)	(5.852)	(2.387)	(2.834)	(3.154)	(2.393)
H-index^2	-0.997***	-2.065***	-2.916***	-3.149***	-1.215**	-1.770***	-2.211***	-2.271***
	(-3.123)	(-6.038)	(-7.416)	(-6.603)	(-2.230)	(-3.362)	(-4.519)	(-3.497)
KZ Index	0.000**	0.000***	0.000***	0.000**	0.000	0.000*	0.000**	0.000**
	(2.052)	(2.859)	(2.617)	(2.575)	(1.517)	(1.950)	(2.313)	(2.287)
Ln(Age)	0.061***	0.052***	0.046***	0.073***	0.122***	0.101***	0.095***	0.135***
	(9.144)	(7.979)	(7.487)	(8.498)	(14.310)	(12.154)	(11.994)	(12.649)
Industry-fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year-fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	38,026	38,026	38,026	38,026	38,026	38,026	38,026	38,026

Table 6: 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 *Ln(1+Patent_value_avg)* and *Ln(1+Patent_value_sum)* is the natural logarithm of one plus the average (sum) of a firm's patent economic value. 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 independent variable of interest is bank geographic diversification (*1−HHI*), which is instrumented using one minus the Predicted value o*f HHI* from the gravity-deregulation model. All other variables are defined in Appendix B. We use heteroscedasticity-robust standard errors and report t-values in the parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Ln(1+Patent_value_avg)				*Ln(1+Patent_value_sum)*			
	t+1	*t+2*	*t+3*	*(t+1, t+3)*	*t+1*	*t+2*	*t+3*	*(t+1, t+3)*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1−HHI	**1.509*** **	**1.290*** **	**0.725** **	**0.601** **	**2.306*** **	**1.935*** **	**1.006**	**0.896*** **
	(3.728)	**(3.453)**	**(2.122)**	**(2.495)**	**(3.250)**	**(2.879)**	**(1.631)**	**(2.825)**
Ln(Sales)	0.329***	0.293***	0.259***	0.177***	0.706***	0.635***	0.561***	0.245***
	(68.461)	(64.364)	(61.411)	(60.629)	(76.158)	(70.832)	(66.409)	(62.478)
PPE	-0.184***	-0.170***	-0.176***	-0.182***	-0.617***	-0.541***	-0.485***	-0.225***
	(-3.056)	(-3.074)	(-3.443)	(-5.531)	(-6.024)	(-5.601)	(-5.460)	(-5.288)
CAPX	0.966***	0.951***	0.823***	0.751***	3.047***	2.802***	2.426***	1.109***
	(4.735)	(5.250)	(4.947)	(7.488)	(8.804)	(8.717)	(8.218)	(8.451)
ROA	-0.013	-0.086**	-0.036	-0.038*	-0.229***	-0.267***	-0.175***	-0.086***
	(-0.274)	(-2.166)	(-1.023)	(-1.691)	(-2.972)	(-3.809)	(-2.770)	(-2.925)
Leverage	-0.349***	-0.350***	-0.312***	-0.208***	-0.704***	-0.689***	-0.607***	-0.266***
	(-11.544)	(-11.657)	(-11.561)	(-10.340)	(-11.650)	(-11.664)	(-11.447)	(-9.918)
Tobin Q	0.073**	0.063**	0.056**	0.031**	0.120**	0.108**	0.096**	0.039**
	(2.013)	(2.012)	(1.991)	(2.035)	(2.047)	(2.038)	(2.014)	(2.050)
H-index	0.609**	0.156	0.198	0.039	1.156**	1.079**	1.654***	0.184
	(2.078)	(0.543)	(0.720)	(0.227)	(2.263)	(2.158)	(3.212)	(0.783)
H-index^2	-1.071**	-0.699	-1.572***	-0.647**	-2.205**	-2.884***	-4.899***	-1.029**
	(-2.094)	(-1.413)	(-3.360)	(-2.180)	(-2.448)	(-3.301)	(-5.256)	(-2.524)
KZ Index	0.000	0.000	0.000	0.000**	0.000	0.000	0.000**	0.000**
	(0.962)	(0.445)	(0.646)	(2.127)	(1.623)	(1.448)	(1.993)	(2.270)
Ln(Age)	0.071***	0.068***	0.064***	0.063***	0.175***	0.155***	0.135***	0.081***
	(7.882)	(8.157)	(8.277)	(11.664)	(10.851)	(10.078)	(9.494)	(11.220)
Industry fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	38,486	38,486	38,486	38,486	38,486	38,486	38,486	38,486

Table 7: Effects of Bank Geographic Diversification on Innovation in Marginal Firms

This table reports the effects of bank geographic diversification on innovation in marginal firms, i.e., small and risky firms, versus non-marginal firms. The dependent variable *Ln(1+Pat)* is the natural logarithm of one plus the total number of patents filed (and eventually granted). *Ln(1+Cite)* is the natural logarithm of one plus the total number of non-self-citations received per patent. Independent variable of interest is bank geographic diversification *(1−HHI)*, which is instrumented using one minus the Predicted value of *HHI* from the gravity-deregulation model. We define large firms as those with firm size (*Size*) greater than the sample median and the rest as small firms. Panel A and B report the results for large and small firms respectively. We define high risk firms as those with firm risk (*Std*) greater than the sample median and the rest as low risk firms. Panel C and D report the results for high and low risk firms respectively. All other variables are defined in Appendix B. We use heteroscedasticity-robust standard errors and report t-values in the parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Large firms								
	Ln(1+Pat)				*Ln(1+Cite)*			
	t+1	*t+2*	*t+3*	*(t+1,t+3)*	*t+1*	*t+2*	*t+3*	*(t+1,t+3)*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1-HHI	**0.390**	**0.280**	**-0.089**	**0.988**	**0.386**	**0.138**	**-0.226**	**0.333**
	(1.100)	**(0.824)**	**(-0.286)**	**(0.834)**	**(1.636)**	**(0.653)**	**(-1.155)**	**(1.107)**
Control Variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Industry fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	19,239	19,239	19,239	17,182	19,239	19,239	19,239	19,239

Panel B: Small firms								
	Ln(1+Pat)				*Ln(1+Cite)*			
	t+1	*t+2*	*t+3*	*(t+1,t+3)*	*t+1*	*t+2*	*t+3*	*(t+1,t+3)*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1-HHI	**3.692*** **	**3.259** **	**2.608** **	**18.952***	**4.928*** **	**3.437** **	**2.560** **	**5.687*** **
	(2.623)	**(2.504)**	**(2.287)**	**(1.842)**	**(2.790)**	**(2.466)**	**(2.256)**	**(2.676)**
Control Variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Industry fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	19,247	19,247	19,247	15,638	19,247	19,247	19,247	19,247

Panel C: High risk firms								
	Ln(1+Pat)				*Ln(1+Cite)*			
	t+1	*t+2*	*t+3*	*(t+1,t+3)*	*t+1*	*t+2*	*t+3*	*(t+1,t+3)*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1-HHI	**1.757*****	**1.518*****	**1.061*****	**6.004*****	**1.547*****	**1.072*****	**0.700****	**2.018*****
	(3.975)	**(3.591)**	**(2.760)**	**(3.490)**	**(4.068)**	**(3.183)**	**(2.385)**	**(4.092)**
Control Variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Industry fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	19,239	19,239	19,239	15,799	19,239	19,239	19,239	19,239

Panel D: Low risk firms								
	Ln(1+Pat)				*Ln(1+Cite)*			
	t+1	*t+2*	*t+3*	*(t+1,t+3)*	*t+1*	*t+2*	*t+3*	*(t+1,t+3)*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1-HHI	**0.207**	**-0.009**	**-0.458**	**-0.408**	**0.695**	**0.248**	**-0.316**	**0.267**
	(0.323)	**(-0.015)**	**(-0.824)**	**(-0.211)**	**(1.466)**	**(0.571)**	**(-0.774)**	**(0.450)**
Control Variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Industry fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	19,246	19,246	19,246	17,021	19,246	19,246	19,246	19,246

Table 8: Channel of Effect: Debt Covenants

This table reports the second-stage of the 2SLS regression results examining the channel effect of debt covenants of loan contracts. *Financial_Cov* is the number of financial covenants, *General_Cov* is the number of general covenants, *Performance_Cov* is the number of performance covenants, *Capital_Cov* is the number of capital covenants, and *Intensity_Cov* is covenant intensity following Bradley and Roberts (2015). The independent variable of interest is bank geographic diversification (*1−HHI*), which is instrumented using one minus the Predicted value of *HHI* from the gravity-deregulation model. All other variables are defined in Appendix B. We use heteroscedasticity-robust standard errors and report t-values in the parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Financial_Cov	*General_Cov*	*Performance_Cov*	*Capital_Cov*	*Intensity_Cov*
	(1)	(2)	(3)	(4)	(5)
1−HHI	**-1.504*** **	**-2.527*** **	**-1.680*** **	**0.037**	**-2.386*** **
	(-4.818)	**(-3.544)**	**(-5.272)**	**(0.223)**	**(-4.619)**
A_Rated	-0.522***	-0.774***	-0.556***	-0.005	-0.428***
	(-33.151)	(-24.078)	(-35.071)	(-0.621)	(-18.009)
B_Rated	-0.057***	0.112***	-0.052***	-0.032***	0.017
	(-4.309)	(3.766)	(-3.837)	(-5.094)	(0.772)
Ln(Loan Amount)	-0.062***	0.002	-0.046***	-0.041***	-0.054***
	(-13.946)	(0.193)	(-10.504)	(-17.029)	(-7.963)
Ln(Maturity)	0.111***	0.322***	0.159***	-0.050***	0.237***
	(15.798)	(20.639)	(21.989)	(-14.306)	(20.966)
Performance Pricing	1.017***	2.099***	0.821***	0.223***	0.354***
	(81.112)	(76.099)	(67.768)	(37.092)	(19.866)
LT2CF	0.001	-0.002	0.002	-0.000	0.002
	(0.873)	(-0.815)	(1.260)	(-0.153)	(0.958)
ST2CF	0.000	0.002*	0.000	-0.000***	0.001*
	(0.729)	(1.903)	(1.253)	(-2.865)	(1.809)
Bank Liquidity	-0.325***	-0.095	-0.208*	-0.098	-0.475**
	(-2.732)	(-0.327)	(-1.680)	(-1.523)	(-2.262)
Credit Spread	-2.625***	-4.159***	-2.095***	-0.503*	-3.567***
	(-4.757)	(-3.093)	(-3.666)	(-1.672)	(-3.659)
Purpose fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Industry fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	36,003	36,003	36,003	36,003	36,003

Table 9: Channel of Effect: Financial Constraints

This table reports the second-stage of the 2SLS regression results on how bank geographic diversification affects the degree of financial constraints in borrowing firms. Financial constraints are proxied by three measures: *KZIndex* is the Kaplan and Zingales (1997) index, *WWIndex* is the Whited and Wu (2006) index, and *SAindex* is the Size-Age index in Hadlock and Pierce (2010). The independent variable of interest is bank geographic diversification (*1−HHI*), which is instrumented using one minus the Predicted value o*f HHI* from the gravity-deregulation model. All other variables are defined in Appendix B. We use heteroscedasticity-robust standard errors and report t-values in the parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *KZindex*	(2) *WWindex*	(3) *SAindex*
1−HHI	**-16.26*** **	**-0.11*** **	**-0.44*** **
	(-7.347)	**(-6.174)**	**(-3.950)**
Ln(Sales)	-0.21***	-0.04***	-0.13***
	(-8.168)	(-175.635)	(-80.895)
PPE	-7.79***	-0.02***	-0.07***
	(-31.015)	(-7.501)	(-5.562)
CAPX	-9.04***	-0.00	-0.01
	(-12.788)	(-0.273)	(-0.127)
ROA	-2.99***	-0.02***	-0.16***
	(-9.440)	(-5.673)	(-13.221)
Industry fixed effects	*Yes*	*Yes*	*Yes*
Year fixed effects	*Yes*	*Yes*	*Yes*
N	38,486	38,153	38,486

Table 10: Bank Geographic Diversification and Technology Spillover– 2SLS Regressions

This table reports the second-stage of the 2SLS regression results showing how bank geographic diversification affects borrowing firms' technology spillover. Dependent variable *Spillover* and *Spillover_Mah* are technology spillover measures. *Spillover* is defined as the natural logarithm of one plus the weighted sum of R&D stock of all other firms, with weight being the cosine similarity of pairwise firm patent portfolio; *Spillover_Mah* is the natural logarithm of one plus the weighted sum of R&D stock of all other firms, with weight being the Mahalanobis metric-based cosine similarity of pairwise firm patent portfolio. Independent variable of interest is bank geographic diversification (*1−HHI*), which is instrumented using one minus the Predicted value o*f HHI* from the gravity-deregulation model. All other variables are defined in Appendix B. We use heteroscedasticity-robust standard errors and report t-values in the parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Spillover				*Spillover_Mah*			
	t+1	*t+2*	*t+3*	*(t+1,t+3)*	t+1	t+2	t+3	(t+1,t+3)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1-HHI	**16.645*****	**12.808*****	**8.369*****	**8.798*****	**24.067*****	**18.284*****	**11.879*****	**12.686*****
	(3.982)	**(3.524)**	**(2.730)**	**(2.946)**	**(4.035)**	**(3.560)**	**(2.766)**	**(3.006)**
Ln(Sales)	0.911***	0.852***	0.779***	0.813***	1.263***	1.173***	1.074***	1.133***
	(28.413)	(30.285)	(32.223)	(34.620)	(27.645)	(29.561)	(31.768)	(34.266)
PPE	-0.469*	-0.253	-0.369**	-0.464***	-0.486	-0.210	-0.349	-0.571**
	(-1.929)	(-1.186)	(-2.055)	(-2.711)	(-1.396)	(-0.696)	(-1.377)	(-2.355)
CAPX	3.428***	3.285***	3.671***	3.285***	4.652***	4.643***	5.109***	4.607***
	(4.827)	(5.332)	(6.831)	(6.703)	(4.623)	(5.336)	(6.812)	(6.727)
ROA	-0.518***	-0.708***	-0.368***	-0.457***	-0.685***	-0.919***	-0.514***	-0.632***
	(-2.916)	(-4.491)	(-2.949)	(-3.762)	(-2.720)	(-4.208)	(-2.981)	(-3.728)
Leverage	-0.970***	-1.301***	-1.096***	-0.955***	-1.346***	-1.746***	-1.536***	-1.282***
	(-5.626)	(-8.829)	(-8.721)	(-7.907)	(-5.456)	(-8.338)	(-8.666)	(-7.467)
Tobin Q	0.128**	0.127**	0.117**	0.117**	0.165**	0.164**	0.149**	0.151**
	(2.110)	(2.071)	(2.005)	(2.077)	(2.137)	(2.095)	(2.022)	(2.104)
H-index	3.770**	3.121**	2.073*	1.700	5.818**	4.406**	3.074*	2.423
	(2.067)	(2.053)	(1.665)	(1.431)	(2.218)	(2.023)	(1.713)	(1.416)
H-index^2	-4.593	-5.096*	-5.771***	-4.205**	-7.525	-7.252*	-8.627***	-6.161**
	(-1.398)	(-1.892)	(-2.670)	(-2.018)	(-1.592)	(-1.870)	(-2.738)	(-2.032)
KZ Index	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-0.515)	(-0.664)	(-0.033)	(-0.233)	(-0.473)	(-0.706)	(-0.089)	(-0.307)
Ln(Age)	0.282***	0.238***	0.201***	0.269***	0.428***	0.377***	0.321***	0.406***
	(6.642)	(6.336)	(6.185)	(8.555)	(7.076)	(7.094)	(7.022)	(9.137)
Industry fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	Yes	Yes	Yes	Yes
Year fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	Yes	Yes	Yes	Yes
N	33,097	33,097	33,097	33,097	33,097	33,097	33,097	33,097

Table 11: Robustness Check: Placebo Test

This table shows the second-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 stage zero. Finally, we estimate the same 2SLS regressions as those in Table 4, instrumenting *(1−HHI)* using one minus the predicted value of HHI from the stage zero model using the falsely assigned deregulation dates. Independent variable of interest is bank geographic diversification (*1−HHI*), which is instrumented using one minus the Predicted value o*f HHI* from the gravity-deregulation model. We use heteroscedasticity-robust standard errors and report t-values in the parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Ln(1+Pat)				*Ln(1+Cite)*			
	t+1	*t+2*	*t+3*	*(t+1,t+3)*	*t+1*	*t+2*	*t+3*	*(t+1,t+3)*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1-HHI	**-0.021**	**-0.060**	**0.034**	**-0.033**	**0.111**	**-0.061**	**0.009**	**0.034**
	(-0.169)	**(-0.494)**	**(0.292)**	**(-0.093)**	**(0.999)**	**(-0.576)**	**(0.090)**	**(0.236)**
Control Variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Industry fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	38,486	38,486	38,486	38,486	38,486	38,486	38,486	38,486

Table 12: Additional Robustness Checks of the 2SLS Regression Result

In panel A, we use the exact same gravity-deregulation model as in Goetz et al. (2013): $Share_{bijt} = \alpha Ln(Distance_{bij}) + \beta Ln(Pop_{it} / Pop_{jt}) + \varepsilon_{bijt}$. *Share* is asset 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; $Ln(Pop_{it}/Pop_{jt})$ is the natural logarithm of the population of BHC's home state *i* divided by population of a foreign state *j* in time *t*. In panel B, we use deposit dispersion as an alternative measure of bank geographic diversification. In panel C, we keep only lead banks while dropping observations in which lenders are participant banks. In panel D, we first estimate the first-stage model and obtain predicted value of *(1−HHI)*. We calculate the average value of the predicted *(1−HHI)* of all BHCs from which a firm borrow in a year, then estimate the second-stage model using firm-year observations, rather than firm-BHC-year observations. Standard errors are heteroscedasticity-robust and t-values are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Ln(1+Pat)				*Ln(1+Cite)*			
	t+1	*t+2*	*t+3*	*(t+1,t+3)*	*t+1*	*t+2*	*t+3*	*(t+1,t+3)*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Using the same gravity-deregulation model as in Goetz et. al. (2013) to construct instrumental variable								
1−HHI	**0.606****	**0.603****	**0.368****	**2.039****	**1.489*****	**1.013****	**0.519****	**2.386****
	(2.186)	**(2.221)**	**(1.408)**	**(2.216)**	**(3.236)**	**(2.292)**	**(1.272)**	**(1.982)**
Control Variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Industry fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	38,486	38,486	38,486	38,486	38,486	38,486	38,486	38,486
Panel B. Using deposit dispersion as alternative geographic diversification measure								
1−HHI	**2.196*****	**2.125*****	**1.299*****	**5.366*****	**3.163*****	**2.211****	**0.486**	**5.741****
	(3.294)	**(3.113)**	**(2.103)**	**(2.485)**	**(3.040)**	**(2.240)**	**(0.540)**	**(2.037)**
Control Variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Industry fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	36,126	34,298	32,569	32,430	36,290	34,495	32,745	32,649
Panel C. Keeping lead banks only								
1-HHI	**1.565*****	**1.627*****	**1.235****	**2.448*****	**1.466*****	**1.191*****	**0.535***	**2.001*****
	(3.057)	**(3.084)**	**(2.502)**	**(3.641)**	**(3.821)**	**(3.265)**	**(1.645)**	**(3.934)**
Control Variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Industry fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	18,879	17,892	16,957	16,900	18,879	17,892	16,957	16,900
Panel D. Estimating stage one and stage two models separately								
Mean(1−HHI)	**1.613***	**2.794*****	**2.498****	**6.505****	**3.691*****	**2.761*****	**1.005**	**3.755*****
	(1.871)	**(2.991)**	**(2.506)**	**(2.429)**	**(3.794)**	**(2.791)**	**(1.022)**	**(3.001)**
Control Variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Industry fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	10,804	10,161	9,539	9,489	10,842	10,205	9,579	9,542

Appendix A: Sample Construction

Step	Sample construction	# of facilities/banks/firms	# of observations
1	Starting with the "lendershares" dataset in Dealscan	188,245 facilities	1,048,575
2	Lenders' names in Dealscan are manually matched to the BHC names among which each BHC has a unique identifier RSSD9001.	122,325 facilities, 297 BHCs (RSSD 9001)	350,569
3	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.	68,331 facilities, 10,947 firms (gvkey)	229,851
4	Merge bank holding company database with the bank Call Report by RSSD9364 to identify assets of each bank subsidiary, then construct BHC geographic diversification measure as the assets dispersion across states based on total assets at bank subsidiary level.	1,165 BHCs	13,098
5	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.	55,291 facilities, 9720 borrowing firms, 203 BHCs	172,126
6	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.	22,201 facilities, 3,886 firm, 162 BHCs	75,901
7	Merge the dataset in step 6 with the CRSP database by permno to retrieve stock returns and market capitalization. After dropping observations with missing values, our final sample contains 38,486 unique bank-firm-year observations over the sample period of 1986-2006.	3,449 firms, 153 BHCs	38,486

Appendix B: Variable Definitions

Gravity-deregulation model	
$Share_{bijt}$	The percentage of BHC *b*'s assets in all subsidiaries in state *j* in year *t* and BHC b is headquartered in state *i*
$LnDistance_{bij}$	The natural logarithm of one plus the straight-line distance between BHC *b*'s headquarter location in state *i* and the capital of state *j*
GSP_home	Gross State Product of a BHC's home state
GSP_foreign	Gross State Product of a foreign state, in which a BHC allocate its asset
CommonBorder	A dummy Variable that equals one if a BHC's home state shares a common land border with a foreign state
HomeState	A dummy Variable that equals to one if a BHC allocates assets in its home state
$Ln(Pop_{it}/Pop_{jt})$	The natural logarithm of the ratio of population of BHC *b*'s home state *i* to that of a foreign state *j* in year *t*.
Main regression	
Pat	Number of patents filed (and eventually granted) in a given year for a firm
Cite	Number of non-self-citations each patent receives in a given year for a firm
Related	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
Unrelated	Number of patents that are unrelated to a firm's core business, computed as total patent counts minus the number of related patents
Patent_value_sum	Sum of the economic value of all patents for a firm with patent values computed based on stock market reactions to announcement of patent grants, following Kogan et al. (2017).
Patent_value_avg	Average of the economic value of all patents for a firm with patent values computed based on stock market reactions to announcement of patent grants, following Kogan et al. (2017).
1−HHI	One minus Herfindale Index of bank assets across states, which measures the actual geographic diversification.
1−Predicted HHI	One minus predicted Herfindale Index of bank assets across states, which is derived from the gravity- deregulation model. It is the instrument variable for the actual geographic diversification.
Spillover	Natural logarithm of one plus the weighted sum of R&D stock of all other firms, with the weight being the cosine similarity of pairwise firms' patent portfolio.
Spillover_Mah	Natural logarithm of one plus the weighted sum of R&D stock of all other firms, with the weight being the Mahalanobis metric-based cosine similarity of pairwise firms' patent portfolio.
Ln(Sales)	Natural logarithm of total sales
PPE	Net property, plants and equipment divided by total assets
CAPX	Capital expenditures divided by total assets
ROA	Net income divided by total assets
Leverage	Total book debt divided by total assets
Tobin Q	(Book value of debt + Market value of equity) / Book value of assets
H-index	Herfindahl index based on segment annual sales using 2-digit SIC codes
H-index^2	Square of *H-index*
KZIndex	Kaplan-Zingales Index, defined as −1.002×cashflow+0.283×tobinq+3.319×debt−39.368×dividend−1.315×cash
WWindex	Whited-Wu index, defined as −0.091×Cash flow+0.062× Dividend dummy+0.021×Long-term debt − 0.044×Size +0.102×Industry sales growth− 0.035×Sales growth
SAindex	Size-Age index, defined as −0.737× Size + 0.043× $Size^2$ − 0.040×Age
Ln(Age)	Natural logarithm of the number of years since a firm appeared in Compustat

Channels of effects	
Financial_Cov	Number of financial covenants
General_Cov	Number of general covenants, including dividend restriction, asset sales sweep, assignment restrictions, collateral release, debt issuance sweep, equity issuance sweep, excess cash flow sweep, insurance proceeds sweep, percentage of excess cash flow, percentage of net income, required lenders, and term changes
Performance_Cov	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
Capital_Cov	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
Intensity_Cov	We follow Bradley and Roberts (2015) to construct covenant intensity index, which covers six categories of covenants including secured debt, dividend restrictions, more than two restricted financial ratios, asset sweep, debt sweep, and equity sweep covenants
A_Rated	Dummy variable that equals one if the borrower has an A, AA or AAA rating from S&P
B_Rated	Dummy variable that equals one if the borrower has a B, BB, or BBB rating from S&P
Ln(Loan Amount)	Natural logarithm of the total amount of loans
Ln(Maturity)	Natural logarithm of time to maturity in months
Performance Pricing	Dummy variable that equals one if the loan spread is tied to a firm's performance and zero otherwise
LT2CF	The ratio of the book value of long-term debt to operating income before depreciation
ST2CF	The ratio of the book value of short-term debt to operating income before depreciation
Bank Liquidity	Bank prime rates minus the contemporaneous federal funds rate
Credit Spread	The spread of Moody's 10-year BAA bond yield over the 10-year AAA bond yield

Appendix C. Calculation of Mahalanobis metric Ω

To address the concern that technology classes may be correlated and technology spillover may occur across technology classes, we follow Bloom et al. (2013), Qiu and Wan (2015), and Tseng (2018) to construct the Mahalanobis distance metric of Jaffe's measure *Tech_Mah*$_{ij}$ as follows:

$$Tech\_Mah_{ij} = \frac{T_i \Omega T_j'}{\sqrt{T_i T_i'} \times \sqrt{T_j T_j'}}$$

Where Ω is a 428×428 Mahalanobis matrix summarizing the correlation of technology classes within firms. The Mahalanobis metric accounts for the possibility that firms internally co-locate in technology classes that generate the greatest knowledge spillovers. More specifically, the calculation of Ω is as follows:

For each technology class ι, we define a vector $\eta_\iota = \left(\frac{T_{\iota 1}}{\sum_i^N T_{\iota i}}, \frac{T_{\iota 2}}{\sum_i^N T_{\iota i}}, \ldots, \frac{T_{\iota N}}{\sum_i^N T_{\iota i}} \right)$ as the patent share of technology class ι across *N* firms. We normalize the vector η_ι and denote it as τ_ι, which is a 1 by N matrix for technology class ι. Next we define a 428×428 matrix Ω to compute the similarity of the 428 technology classes, with $\Omega = \tau\tau'$, where τ is a 428×N matrix for all technology classes, and Ω is a 428×428 matrix of similarity with each element being the pairwise similarity between each pair of technology classes.