Innovating Banks and Local Lending

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ABSTRACT

We study the effects of financial and technological innovation by banks on local competition for deposits and credit supply. Banks that innovate increase their local market power by gaining deposits in a zero sum game at the expense of local non-innovating competitors. Innovative banks make use of both the additional liquidity as well as process innovations itselves and expand aggregate local mortgage lending. Banks allocate their additional funding efficiently with loan performance improving for banks that innovate. We employ two instrumental variable approaches that relate the number of patents awarded to a bank holding company to the human capital available to the bank as well as to the leniency of patent examiners to identify the causal effect of bank innovation on deposits and lending.

Keywords: Innovation, Financial Technology, Competition, Branch Banking, Credit Supply.
JEL Classification Numbers: G20, G21.

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1 Introduction

Digitalization in the financial sector has recently led to a sharp rise in the number of fintech startups that challenge traditional banks by relying on technological innovations. These startups try to compete with banks by offering new, more convenient, and faster services and by decreasing the costs of operations. Banks, on the other hand, have reacted to this growing competition by streamlining their operations (i.e., in many cases, downsizing their branch networks) and employing technological innovations themselves, either through expanding their own R&D efforts or by acquiring innovative fintechs. This digital revolution in banking has closely followed another development that has been reshaping the financial industry for the past decades: a steep increase in financial innovations. However, while research has covered the latter extensively over the years, technological innovation in banking and its benefits for lenders and the banks themselves remain virtually unexplored.

In this paper, we show that innovating banks raise more deposits via their branch networks and grant more mortgage loans. Bank branches that profit from innovations awarded to their holding company are able to attract deposits (and thus customers) in a zero sum game at the expense of local non-innovating competitors. This effect is more pronounced in counties in which non-innovative banks branches dominate the market and are challenged for the first time by an innovative competitor. In contrast, counties in which only branches of innovative banks compete with each other experience no shifts in market shares and deposits. Innovative banks then make use of this additional liquidity, as well as the innovations in processes, operations, and online/mobile banking itselves, to expand mortgage lending. However, rather than just taking lending business away from non-innovators, innovating banks also increase aggregate lending which increases with the share of innovative banks that have a branch presence in a contested county. In line with the notion of innovators driving out less innovative, less efficient competitors, banks that innovate are able to attract more loan applications, attract better loans, and thus increase their overall loan performance. Combined, our results provide evidence for the importance of (especially technological) innovations in banking.

We start our analysis by first documenting a steadily increasing trend in the number of patents awarded to U.S. bank holding companies (BHCs) in recent years. This trend is not due to an increasing number of financial innovations, but due to a rapidly increasing number of technological advances in all areas of banking (see also Lerner, 2002). In fact, the number of newly awarded financial patents has been declining since the financial crisis while the number of awarded technological patents still increases. We manually categorize banks' patents and see a clear trend with some banks investing massively in the efficiency of their internal processes, their online and mobile banking, as well as their IT operations. We then show that innovation in general significantly increases BHCs' overall lending, deposit taking, and branch network size, while at the same time driving down the cost of their deposits. To identify how innovative banks are able to expand lending and attract deposits, we turn to an in-depth analysis of the effect of innovation on bank performance at the branch level.

The identification of the causal effect of innovations by BHCs on lending behavior at their local branch level is challenging for a number of reasons. For example, innovation and firm outcomes at the holding level will be simultaneously determined by financial constraints that directly affect both a bank's lending ability on the one hand, and, on the other hand, its R&D expenditures (and thus a main input factor for generating innovation) as well as its willingness to innovate in the first place. We address this problem by employing two instrumental variable (IV) approaches. Our first instrument variable is founded in a rich literature that relates a region's human capital to local firms' innovation (see, e.g., Glaeser et al., 1995; Moretti, 2004; Carlino et al., 2007; Florida et al., 2008; Abel and Deitz, 2012) as well as studies that highlight the impact of managerial education on firm outcomes (Malmendier and Tate, 2005; Schoar and Zuo, 2017, see, e.g.,). Based on these findings, we instrument for a bank's decision to innovate by employing the number of PhDs completed in a metropolitan area as a proxy for the human capital available to banks headquartered nearby. In our second IV approach, we follow Gaulé (2018) and instrument for the number of patents awarded to a BHC by using differences in leniency across banks' patent examiners as a plausibly exogenous source of variation in the probability of being granted a patent. We then use these instruments in alternative regressions to verify the causal effect of patents on banks' lending. Next, the causal relation between bank innovation and lending at the local level will not only suffer from reverse causality, but also be confounded by local demand effects. Moreover, a region's human capital and local lending could be jointly determined thereby violating the exclusion restriction for the former's use as an instrumental variable. We address these concern in two ways. First, by analyzing the changes in bank lending in counties outside a BHC's headquarters state/county, we alleviate concerns that local demand for loans simultaneously drives both lending and innovation (as well as our IV). Second, we follow Gilje et al. (2016) and estimate our panel regressions with region*year (and, alternatively, county*time) fixed effects to control for time-varying local demand effects.

Why are innovating banks able to increase their lending compared to non-innovating banks? Even though traditional theories of growth and innovation starting with Schumpeter's idea of creative destruction (see Schumpeter, 1942) emphasize the beneficial effects of firm innovation, it is not immediately clear how innovations help banks to expand credit. Financial and technological innovations could help banks overcome two financial constraints that prevent them from pursuing profitable loan investments. First, on the bank's asset side, technological and process innovations in screening processes, loan monitoring, and credit risk management could lower asymmetric information and reduce costs thus giving innovating banks a competitive advantage over their non-innovating competitors. In addition to this, financial innovations in the form of new products and improved bank marketing could attract new customers. Second, on the bank's liability side, innovations could improve banks' access to finance. For example, financial innovations and subsequent improvements in risk management could lower a bank's risk exposure and free-up regulatory capital. Moreover, more innovative bank marketing and improved, digitalized processes in online and mobile banking could help the bank attract more depositors thereby getting better access to external financing. We show that both views hold empirically with more innovative banks having lower financing costs and better loan performance.

Our findings contribute to several different strands of the literature. First, our paper significantly extends the research on innovation by financial institutions. By now, an extensive literature has highlighted the importance of new and improved financial products and services for enabling firms inside and outside the financial sector to raise more capital at reduced cost (see, e.g., Miller, 1986; Tufano, 1989; Merton, 1992; Tufano, 2003).[1] Interest in financial innovations surged even more after the 1998 appellate decision in State Street Bank and Trust v. Signature Financial confirmed the patentability of financial formulas (see Lerner, 2002). Since then, various theoretical (see, e.g., Laeven et al., 2015) and empirical studies (see, e.g., McConnell and Schwartz, 1992; Grinblatt and Longstaff, 2000; Lerner, 2006) have stressed the beneficial effects of financial innovations.[2] To the best of our knowledge, however, there is little to no evidence yet on the effect of technological innovations by banks.[3] In this paper, we first show that not only has the number of financial patents awarded to US banks been decreasing since the financial crisis, but also is the number of technological patents by banks strongly increasing. We then find that innovations in banking cover a broad range of areas with the majority of awarded patents being related to banks' efforts to improve payment services (esp. ATMs), online/mobile banking, loan screening and processing, as well as general IT operations. As our sample covers the majority of the US banking sector, our results show how seasoned traditional deposit-taking banks (and not just fintech startups) profit from innovations.

Second, our paper is also related to an extensive literature on the drivers of bank lending and borrower-lender proximity. Even though technological advances and online banking have decreased the importance of a close proximity between a bank and its borrowers (see Petersen and Rajan, 2002), local and relationship banking still play an important role especially in the US with small firms relying heavily on small, local banks (see, e.g., Berger et al., 2005; Berger and Kim, 2017) while larger companies have access to financing from large, distant lenders (see Degryse and Ongena, 2005; Agrawal and Hauswald, 2010). One reason for this

[1]For even earlier works on financial innovations, see, for example, the studies by Silber (1975); Ben-Horim and Silber (1977); Silber (1983)

[2]Few, but notable exceptions by Henderson and Pearson (2011) and Beck et al. (2016) find empirical evidence for the opposite view that financial innovations can lead to higher bank fragility as well as introduce unnecessary complexity into financial products to exploit uninformed investors.

[3]Notable recent exceptions are due to, e.g., Berg et al. (forthcoming); Chen et al. (2019) and Fuster et al. (2019). However, while these studies concentrate on the role of financial technology, none of them looks at the aggregate effects of innovations on bank lending.

importance of local banks can be seen in their competitive advantage over outside lenders (see Loutskina and Strahan, 2011) and large banks (see Hombert and Matray, 2016) in screening and monitoring local, opaque borrowers. As shown by Gilje et al. (2016), a key ingredient for banks to secure such competitive advantages both in lending but also in deposit-taking is the existence of a branch presence in the proximity of its customers. Innovation, however, especially in the form of technological patents, could significantly disrupt this picture. As technology could substitute for local proximity (in the form of a branch presence) between a bank and its borrowers, more innovating banks could be inclined to reduce their number of branches and thereby cut costs. We find that the opposite is the case. Innovation at the holding level translates into increased loan and deposit growth together with a significant decrease in financing costs and an increase in the number of branches.

Finally, our paper reveals a new facet of the bank lending channel. While most of the previous studies on the effects of credit expansion on economic growth have used supply-side shocks to banks' liquidity (see, e.g., Kashyap and Stein, 2000; Campello, 2002; Loutskina and Strahan, 2011) or regulatory interventions (see, e.g., Paravisini, 2008; Iyer and Peydro, 2011; Gropp et al., 2019) for identification, we study how innovations enable banks to expand their lending. A critical advantage of this approach is that our identification does not rely on a common sector-wide shock to liquidity, capital, or regulation, but instead relies on the idiosyncratic innovative power of some banks compared to others. To establish the causality running from bank innovation to bank deposits and loans in our instrument variable regression, we build on a rich literature on innovation management and exploit the fact that human capital exogenously drives banks' innovations but not directly affect deposit-taking and lending in remote bank branches. To give our main results even more credibility, we make use of a second instrument that is completely unrelated to the realm of banking. Using the leniency of patent examiners as an instrument for a bank's probability to be granted a patent, we again find strong empirical evidence for a positive and significant effect of bank innovation on deposit growth and lending.

The remainder of the paper is structured as follows. Section 2 briefly describes our data. In

Section 3, we present our empirical strategy including our instrument variable approach used for identification. Section 4 presents our empirical results, while Section 5 contains a short summary of our findings and a conclusion.

2 Data and sample construction

As we outline in Section 3, our identification strategy is based on instrumenting banks' innovation activities with the human capital available near the BHC's headquarters and studying the causal effects of innovation on bank outcomes at the local bank-branch level. Consequently, we merge several data sets at the bank- and bank-branch level together with patent office data to form our final sample. All variables are defined in Appendix I.

2.1 Bank data

We start the construction of our sample by first taking the universe of U.S. bank holding companies in the period between 1997 to 2014. We compile balance sheet and income data from year-end Call Reports for all BHCs that are regulated by the Federal Deposit Insurance Corporation (FDIC), the Federal Reserve (FED), and the Office of the Comptroller of the Currency (OCC). Accounting variables at the BHC-level are later used in our regressions of the deposit and mortgage growth at the branch-/county-level to control for bank characteristics that may affect both a bank's innovation-related productivity as well as its performance in terms of financing and lending activities.

Next, we collect loan application data for each bank-county observation using the Home Mortgage Disclosure Act (HMDA) dataset. We merge the aggregated HMDA loan application data with the annual Call Reports of each BHC in our sample. More precisely, we use the HMDA bank identification number and match it with the FDIC certificate ID (RSSD9050) for banks reporting to the FDIC, the Call Report identification number (RSSD ID) for banks reporting to the Federal Reserve, and the Call Report item (RSSD 9055) for banks reporting to the OCC. The introduction of the Dodd-Frank Wall Street Reform and Consumer Protection Act in 2010, however, resulted in a change in some of our banks' supervisory agency. To control for this change in agencies, we additionally consider the Consumer Financial Protection Bureau (CFPB) to uniquely match banks from the Call Reports to banks in the HMDA loan application data for observations after 2010. We only consider banks making housing-related loans (i.e., home purchase mortgages, mortgages for refinancing, and home equity loans, Loutskina and Strahan (see also 2009); Gilje et al. (see also 2016, for a similar preparation of the data)) but do not restrict our sample geographically and thus consider banks from all U.S. states. From the HMDA data, we then employ information on a bank's mortgage lending activity within a given county regardless of whether it has a branch presence in that respective county or not. The available data on borrowers/applicants are used as additional control variables in our regressions of the banks' lending.

Finally, we match our data to the Summary of Deposits database from the FDIC to enrich our sample with information on each bank's number of branches and the amount of deposits held via each of its branches in the U.S. during our sample period. Our final sample then consists of 450,363 bank-branch-year observations (mortgage loan data) and 148,226 bank-county-year observations (deposit data) with 1,984 unique bank holding companies.[4]

2.2 Proxies for bank innovation

For each BHC, we collect bank-year patent and citation information from the U.S. Patent and Trademark Office (USPTO) patent assignments record and from the USPTO Application Information Retrieval (PAIR) database. We compile our data on patents directly from the USPTO as recent studies (see Gao and Zhang, 2017; Moshirian et al., 2019) have shown a slightly better coverage of (U.S. firms') patents in the USPTO databases than in the National Bureau of Economic Research patents database.[5]

To proxy for a bank's innovation productivity, we use two variables based on a bank's patents.

[4]While the HMDA data on the sample banks' mortgage loans is available at the bank-county-level, the FDIC's data on the deposits held by a BHC are available at the bank-branch-level.

[5]http://patft.uspto.gov/netahtml/PTO/index.html and https://portal.uspto.gov/pair/PublicPair.

The first measure is a bank's number of (eventually granted) patents filed in a given year. We follow related studies in the innovation literature and use a patent's application year instead of its grant year to better capture the time of the innovation (see, e.g., Griliches et al., 1988; Cornaggia et al., 2015) Furthermore, we assume that banks have zero patents if they are not matched to the database. To ensure that we are able to identify the final status of patent applications, we follow Hall et al. (2001) and end our sample in 2014 (the end of our sample thus also coincides with the last year with available HMDA data).[6]

While the number of granted patent applications is a natural choice for a bank's overall innovation productivity, it does not distinguish between true innovations and only incremental findings. As such, we employ a second proxy for bank innovation (*Citations*) by taking the number of nonself citations a patent receives in the application year (see also Hall et al., 2001, 2005; Tian and Wang, 2011; He and Tian, 2013). Moreover, we use two additional innovation measure that take the number of nonself citations a patent receives in *all* subsequent years (variable *Long-Term Citations*) as well as in the five years after the application year (variable *Short-Term Citations*). For all measures of innovation quality, we compute the respective proxy by taking the sum of the mentioned citations across all patents of a bank per year. While we employ our measure of innovation productivity in our baseline analyses, our three measures of innovation quality are used to check the robustness of our findings.[7]

2.3 Descriptive statistics

Figure 1 exhibits the time evolution of the patents granted to U.S. BHCs during our sample period. In total, our sample includes a total number of 2,243 patents that were applied and later granted to 29 distinct BHCs.[8]

[6]In contrast to previous studies that show a two-year lag between patent application and patent grant, on average, the bank patents in our sample are characterized by an average lag of about 3.5 years between the times a patent is applied and later granted.

[7]Using a bank's total future citations and total patents in a year, we also employ the variable *Citation-Weighted Patents* in our robustness checks.

[8]Note that our sample includes, and is almost three times larger than the fintech patent sample identified for banks by Chen et al. (2019). In contrast, their full sample includes a considerable number of patents awarded to non-bank

[Place Figure 1 about here]

Panel A of Figure 1 shows that the average number of patent applications by banks increased steadily to more than 300 patents in 2013. Banks in the U.S. filed for less than ten patents per year until the millennium, at which point application numbers surged. Innovation activity saw a slight downward trend during the financial crisis but immediately recovered with the number of applied patents increasing again by 2010.

To get a better understanding of the nature of innovations by banks, we first divide the universe of banks' patents into two broad subcategories: financial and non-financial patents. For this, we follow Lerner (2002) and consider as *Financial Patents* those that were filed in the patent classes 705/35 (Finance), 705/36 (Portfolio selection, planning, or analysis), 705/37 (Trading, matching, or bidding), 705/38 (Credit risk processing or loan processing), and 705/4 (Insurance) (see also Lerner et al. (2015)). Conversely, the remaining patents that do not belong to these classes are considered to be *Non-Financial Patents*.[9]

Panel B of Figure 1 plots the time evolution of patents by categories (financial vs. non-financial). The plot shows that the number of financial and non-financial patents remains at a constant low level until the year 2000. After 2000, the numbers of granted financial and non-financial patents applications evolve quite differently. On the one hand, the number of financial patents experiences a small increase until 2010 and then sharply declines in subsequent years. Non-financial patents, on the other hand, become more relevant. The average number of non-financial patent grants increases to 167 shortly before the financial crisis and slightly decreases thereafter. After this small dip, the number of non-financial patent grants increases again to its maximum of 349 non-financial patents in the final year of our sample. In total, banks apply for 457 financial and 1,786 non-financial patents.

The broad categorization of banks' patents into financial and non-financial (i.e., process) innovations is helpful to get a first impression of the innovative activities of banks, but dates back

entities.

[9]Different (and finer) classifications of banks' patents are of course possible, see e.g. Chen et al. (2019) for a finer categorization of fintech patents. As we consider the universe of patents awarded to banks, however, we opted to employ broad categories for our patents to avoid binning the patents into too many patent subclasses.

to a pre-fintech time in which non-financial patents were rare to non-existent in the financial sector. To better understand in which areas of their business banks innovate, we further categorize all bank patents into subcategories. We start by manually identifying those patents that propose, or are related to financial product innovations (such as new types of derivative contracts). Next, as additional subcategories, we identify and count patents in patent subclasses that are related to credit risk processing (705/38) and portfolio selection and trading (705/36, 705/37). Especially near the end of our sample period, a large number of innovations are related to improvements in a bank's back office operations and IT infrastructure. We therefore manually screen the titles and descriptions of the patents to identify patents that propose such innovations. At the frontend of a bank's business, we also observe a large number of patents on online/mobile banking. Thus, we again screen patent grants manually and identify those patents that are clearly related to improvements of online or mobile banking processes. Finally, a significant number of bank patents propose improvements in automated teller machines (ATMs), account management, and payment services in general. In summary, we end up with six subcategories in which all our sample bank patents can be classified.

[Place Figure 2 about here]

Figure 2 shows the time evolution of the number of granted bank patents in each of our six patent categories. Three trends are clearly visible: first, a constant but low (and later in our sample period decreasing) number of financial product innovations and classical finance-related innovations (e.g., in trading and portfolio management) are granted to U.S. banks. Second, over our whole sample period innovations related to ATMs and payment services saw an increasing trend until the mid 2000s and have been decreasing again since then. Third, and most importantly, the vast majority of patents awarded to U.S. banks are the result of technological innovations in the banks' online/mobile banking and its IT operations and infrastructure. Figure 2 thus clearly highlights the technological revolution in the banking sector well before the advent of blockchain and cryptocurrencies.

Table I reports summary statistics for our sample of innovating, i.e., banks applying for patents, and non-innovating banks. Panel A of Table I provides information on banks' patents. On average, the sample of innovating-banks have applied for 22 patents, that can be subdivided into 5 financial and 17 non-financial patents. When looking at the detailed patent categories, our findings reveal that banks apply for patents that are predominantly related to operations/IT, online/mobile banking, and ATMs.

Panel B provides summary statistics for BHC's financial statement characteristics. The table shows that innovating banks tend to be larger than non-innovating banks and that they rely more on non-traditional banking activities, i.e., they have a higher non-interest income to total income ratio. Banks that do not apply for any patent have on average higher loan and deposit ratios than patenting banks. However, the performance ratio ROA is comparable between innovating and non-innovating banks. The variables in Panel B come from year-end Call Reports, except Interest Expenses/Deposits, Deposit Growth, and Total Loans Growth that are measured in year t.

Panel C shows summary statistics on banks' mortgage activity data. Data in this Panel is annually collected from the Home Mortgage Disclosure Act (HMDA) which we merge with Call Report data as in Gilje et al. (2016) and Gilje et al. (2015). The HMDA database allows us to locate information about borrowers' loan applications, the loan amount, the information about loan approval or the rejection reason, the identity of the lender, the location of the property and the geographical location of the borrower. In accordance to Gilje et al. (2016), we consider information on borrowers' income, the loan size to income ratio and both the percentage of women and minority applicants. Panel C shows that the mortgage growth level of innovating banks is on average 10.4% while non-innovating banks show an average mortgage growth level of -6.1%. Also, innovating banks have a higher loan-size-to-borrower-income ratio (1.77%) while non-innovating banks display a loan-size-to-borrower-income ratio of 1.61%. The percentage of female applicants and minorities are 40% and 15% for innovating and 21% and 7% for non-innovating banks, respectively.

In Panel D we provide additional information about county control variables, i.e., the percentage of minorities in a county and the income per capita ratio in a county. Data is retrieved from Census data of the National Bureau of Economic Research (NBER) and shows average county-year measures. Panel E shows the average number of doctoral degrees. Data is provided on MSA-year level and is retrieved from the National Science Foundation and the Higher Education Research and Development Survey (HERD).

3 Identification Strategy

We analyze how variation in the level of innovation at BHCs affects deposit growth, lending, and loan performance. As the relation between bank innovation and our branch-level outcome variables will most likely be endogenous due to being simultaneously determined by omitted variables at the BHC and the branch level, we try to identify the causal link between bank innovation and branch-level outcomes by using two complementary empirical strategies.

In our first instrumental variable approach, we employ the availability of human capital in the vicinity of a BHC's headquarters as an instrument for bank innovation. In particular, we estimate the two-stage regression model

$$\begin{aligned} Innovation_{i,l,t} &= \alpha_1 Human\ Capital_{l,t-1} + \alpha_2 \mathbf{x}_{1,i,l,t-1} + \alpha_3 \mathbf{x}_{2,j,t-1} \qquad (1) \\ &+ \gamma_i + \eta_t * \lambda_k + \varepsilon_{i,b,j,k,l,t} \\ Outcomes_{i,b,j,k,l,t} &= \beta_1 \widehat{Innovation}_{i,l,t-1} + \beta_2 \mathbf{x}_{1,i,l,t-1} + \beta_3 \mathbf{x}_{2,j,t-1} \qquad (2) \\ &+ \gamma_i + \eta_t * \lambda_k + \epsilon_{i,b,j,k,l,t} \end{aligned}$$

where i indexes a BHC headquartered in Metropolitan Statistical Area (MSA) l operating branch b in county j in region k in year t. The dependent variable $Innovation_{i,l,t}$ in our first stage regression is one of various proxies for firm innovation based on a BHC's patents. $Human\ Capital_{l,t}$ is our main instrument variable defined as the average number of doctoral degrees awarded in year t in MSA l. Data on the total number of awarded doctoral degrees in a

MSA per year is retrieved from the National Science Foundation and the Higher Education Research and Development Survey. Our main focus lies on the estimates for the parameter β_1, the effect of bank innovation at the BHC level on our outcome variables $Outcomes_{i,j,k,l,t}$ at the bank branch level. The crucial assumption for a valid identification of any causal effect of bank innovation on bank deposit-taking and lending is the orthogonality of human capital in a BHC's home MSA to the error term in our first stage regression. In other words, human capital must only affect local financing and lending by providing the BHC's headquarter with employees who in turn innovate. In the following, we discuss several steps we take to justify that our instrument fulfills the exclusion restriction.

First, the exogeneity of our instrument could be violated if the business activities of bank branches would spill over to the BHC causing reverse causality. Additionally, overall business success of a BHC could spur growth in its home MSA leading to more people moving to this MSA, pursuing degrees in higher education, etc. Although it is unlikely that individual branches of a bank could have such an effect on the BHC (and subsequently its home area), we control for such a confounding effect by including a vector $\mathbf{x}_{1,i,l,t-1}$ of lagged idiosyncratic covariates at the BHC level and a second set $\mathbf{x}_{2,j,t-1}$ of lagged controls at the county-level in our regressions. In those regressions in which we employ the mortgage growth of a bank branch as the outcome variable, we additionally control for a vector $\mathbf{x}_{3,i,b,j,t}$ of contemporaneous borrower controls. Finally, we employ BHC-fixed effects to control for unobserved factors co-determining bank innovation and estimate all our regressions using robust standard errors.

Second, our proxies for human capital and bank innovation could be spuriously correlated in case both variables are co-determined by omitted local factors in the BHC's home area. While trends in economic growth that could drive both innovation and human capital should be captured by the time-fixed effects in our regressions, these confounding effects will most likely differ from MSA to MSA. We address this concern in two ways. First, in addition to our main regressions, we perform robustness checks in which we exclude those branch observations that are located in the respective BHC's home state (county). As a result, local factors that drive outcomes at the

BHC level should not simultaneously drive branch level outcomes outside the bank's home state (county). Second, we further mitigate the concern of a spurious correlation caused by unobserved local factors by running regressions in which we include state*time fixed effects based on a BHC's home state. Our approach ressembles the idea by Gennaioli et al. (2012) who argue in their study on country differences in economic development that human capital together with institutions can be regarded as exogenous with respect to economic growth as long as one controls for country-fixed effects. Their empirical strategy is criticized, however, by Acemoglu et al. (2014) who argue that institutions and human capital will vary both regionally and across time. By using state*time fixed effects in our robustness checks, we reconcile both views in our setting as our approach allows us to control for time-varying differences in local institutions and economic growth.

Third, the validity of the exclusion restriction requires that not only local factors near the BHC's headquarter, but also the local economic environment of a bank branch (and most importantly average personal income and the demand for loans in a county) must not affect our outcomes and bank innovation at the same time. To address this concern, we take up the idea of Gilje et al. (2016) and saturate our panel regressions with region*year fixed effects to control for time-varying local demand effects.[10] Moreover, our robustness checks in which we only include bank branch observations that are geographically distant from the respective BHC's headquarter should also mitigate the concern of an omitted variable bias stemming from local demand effects.

We then complement our main empirical strategy by a second instrumental variable approach in which we make use of exogenous variation in the probability that a patent applied by a bank is ultimately granted. More precisely, we follow Gaulé (2018) and first estimate the overall leniency of patent examiners as an instrument for the number of patents granted to banks. The USPTO assigns patent application first to one of eight Technology Centers (TC) in which applications are given a technological classification and, based on this classification, assigned to an art unit. Within the art unit, a Supervisory Patent Examiner (SPE) will then assign the application to a patent examiner who will decide on the application (see Cockburn et al., 2002). This process of matching

[10]We follow Acharya et al. (2012) and use the definition of the U.S. Census Bureau that distinguishes four U.S. regions, i.e.: Northeast, South, Midwest, and West.

applications to patent examiners provides us with a plausibly exogenous variation in the likelihood of a bank being awarded a patent and we use the resulting variable, $Examiner\ Leniency$, as an instrument for bank innovation.[11]

To retrieve information on the examiner of each patent application in our sample, we use data from the USPTO patent assignments record. For each patent application (which is later granted), we retrieve the Examiners-ID and the art unit the application is assigned to. The American Inventors Protection Act (AIPA) requires that inventors that apply for patents at USPTO on or after November 29, 2000, to publish their applications one and a half year after the filing date. Prior to November 2000, however, USPTO did not publish patent applications (see Graham and Hedge, 2015). Therefore, we only consider patent applications that were filed after January 2001, in order to be consistent with our sample.

To measure examiners' leniency, we follow Gaulé (2018) and estimate the following equations:

$$E_{p,t} = \frac{Grants_{q,u,t} - 1}{Applications_{q,u,t} - 1} \tag{3}$$

and

$$U_{p,t} = \frac{Grants_{u,t} - 1}{Applications_{u,t} - 1} \tag{4}$$

We consider a patent application p that is filed in year t, allocated to art unit u and examiner q. $Grants_{q,u,t}$ is the number of granted applications by examiner q that were filed in year t. $Applications_{q,u,t}$ represents the total number of patent applications in year t assigned to examiner q. $Grants_{u,t}$ is the number of patents filed in year t and granted by art unit u, while $Applications_{u,t}$ is the number of applications filed in year t and assigned to art unit u. The difference between $E_{p,t}$ and $U_{p,t}$ represents the difference between the leniency of an examiner and the average leniency

[11] Righi and Simcoe (2019) argue that while some SPEs assign patent applications randomly to examiners, some might favor technological specialization in the examiners in their TC. They argue that this could invalidate the use of patent examiner leniency as an IV if used across TCs in studies of industrial firm innovation. However, as we concentrate on a very narrow subsample of patents within few technological patent subclasses, the matching within these subclasses should be sufficiently random for our IV to fulfill the exclusion restriction.

applicants are confronted with when applying for a patent in year t in art unit u. If a bank i applies only for one patent in a year, we use the difference between $E_{p,t}$ and $U_{p,t}$ as our instrument $Examiner\ Leniency_{i,t}$ for the probability of an application to be granted. If a bank applies for more than one patent per year, we average the difference between $E_{p,t}$ and $U_{p,t}$ across all patents p applied by bank i in year t. Using this second IV, we then estimate a two-stage regression model in which we substitute the first stage as shown above by the alternative estimation

$$\begin{aligned} Innovation_{i,l,t} &= \alpha_1 Examiner\ Leniency_{i,t} + \alpha_2 \mathbf{x}_{1,i,l,t-1} + \alpha_3 \mathbf{x}_{2,j,t-1} \\ &+ \gamma_i + \eta_t * \lambda_k + \varepsilon_{i,b,j,k,l,t}. \end{aligned} \tag{5}$$

A caveat of our second IV strategy is that our instrument $Examiner\ Leniency$ can only be estimated for banks that have applied for at least one patent during our sample period. Apart from the apparent effect that this reduces our sample size, we are also only able to interpret the results from our second stage IV regressions as a local treatment effect on the subsample of banks that have chosen to innovate. Nevertheless, this second identification strategy allows us to show that the degree of a bank's innovativeness, in addition to the bank's general decision to innovate, has a causal effect on bank outcomes.

4 Results

4.1 Baseline Results - BHC Level

We start our investigation into the effects of innovation on bank performance by performing regressions of bank outcomes at the bank level. In particular, we try to explain a bank's overall growth in total loans, its deposit supply as proxied by the growth rate of deposits, the growth in the number of braches, the price of deposit funding (interest expense on deposits/deposits), and its overall return on assets (ROA). We saturate our regressions at the BHC level with lagged bank controls as well as bank and year fixed effects and employ robust standard errors. Our main explanatory variable in all these regressions is the lagged number of patents granted to a bank.

[Place Table II about here]

As can be seen from Table II, bank innovation is significantly positively correlated with banks' overall lending, deposit supply, and negatively correlated with the costs of deposit funding. The magnitudes of these effects are also highly economically significant. For instance, a one standard deviation increase in the (log) number of patents is associated with a 67 basis points (BP) higher yearly loan growth (see column (1), $0.1945 * 0.0347$). Similarly, a one standard deviation increase in innovation will lead to a 71 basis higher growth rate in deposits (see column (2), $0.1945 * 0.0366$) and costs of deposit financing that are 7 BP (see column (4), $0.1945 * -0.0036$) lower. Interestingly, innovation by banks does not automatically lead to a reduction in banks' branch networks as the number of patents is positively correlated with the growth rate of branches, neither does it significantly affect a bank's profitability as measured by its ROA.

The results from Table II point to the idea that innovative banks take in more deposits, are able to decrease their financing costs, and as a result extend their credit supply. To refine our investigation into the effects of bank innovation and to establish a causal link between banks' patenting activities and lending, we take our analysis to the local branch level and estimate regressions as laid out in Equation (3).

4.2 Baseline Results - Local Deposits

We begin our analysis at the local level by estimating regressions of the growth in deposits by bank-county-year on the (log) number of patents. Table III presents the results from ordinary least squares (OLS) regressions as well as the first and second stage results from IV regressions using $Human\ Capital$ as our instrument.

[Place Table III about here]

The results show a statistically significantly positive effect of innovation on local deposit growth. A one standard deviation increase in the (log) number of patents leads to a 67 BP (see column (2), $0.2065 * 0.0323$) increase in deposits per year. As expected, our instrument variable is strongly and positively correlated with our innovation proxy and passes the Kleibergen-Paap test for weak instruments. The OLS point estimate in our full sample has the same sign, the same statistical significance, and is of the same magnitude as the one in our IV specification. In other words, we do not find any evidence of either a "corrective" or an "affirmative endogeneity" (cf. Jiang, 2017), providing us with further evidence that our estimation does not suffer from a weak instrument.

We next decompose our main explanatory variable $Patents$ into our six previously defined categories of bank innovations to answer the question which type of innovation drives the found increase in local bank deposits. Results from regressions of the growth rate in local bank deposits on the numbers of patents in the different categories are given in Table IV

[Place Table IV about here]

In columns (1) through (6) of Table IV, we employ each patent category individually and instrument for bank innovation. The six patent category variables correlate quite strongly (and positively) with each other with some of the variables exhibiting a correlation of up to 94.5% (ATM and Online/mobile banking patents). Using each patent category variable on its own will thus produce an omitted variable bias if the remaining patent variables are not included in the regression. However, as with the total number of bank patents, our variables capturing the innovation of banks in the six different technological fields will also suffer from the described endogeneity problems. As instrumenting for six endogenous variables at the same time is not feasible in our setting, we resort to an OLS estimation in column (7) in which we include all six patent categories at the same time.[12]

The results presented in Table IV show that when taking individually, all six patent categories have a positive and statistically significant effect on banks' local deposit growth as our dependent

[12] As described earlier, IV estimates do not deviate too strongly from OLS estimates, with the former usually being slightly larger in magnitude than the latter. Even though we do not instrument for our six patent category variables in column (7) of Table IV, we believe that the OLS coefficients will likely underestimate the true effect of innovation types on deposit growth.

variable. The OLS estimation described in column (7), in which we employ all six patent variables simultaneously, however, shows a different picture. As soon as we control for the innovations in other technological fields, we see the significance of the innovation proxies vanish for all but the back office operations/IT category. The effect of process and IT innovations on banks' ability to take in deposits is also highly economically significant with a one standard deviation increase in patents in this category is associated with a 2.3% higher annual deposit growth (see column (7), $0.8474 * 0.0276$). This result is not surprising for the following two reasons. First, as can be seen from Figure 2, there seems to be a significant time lag between the advent of innovations in banks' processes/IT systems and innovations at their front-end customer interface (most notably, ATMs and online/mobile banking). While the number of patents in the former category started to increase around the millenium, patents in the latter categories only started to lift off around 2005/2006. Consequently, the result from column (7) could be indicative of a first-mover advantage with patents in the back operations/IT category flagging those banks that started early on to innovate.[13] Second, patents in the category of bank office operations/IT systems are often of an improving character, rather than breakthrough innovations. Nevertheless, they could have laid the grounds for later innovation with banks starting off their R&D activities by improving their existing processes and systems before moving on to more customer-related new products and process innovations. Anecdotal evidence from manually inspecting all patent applications in our sample supports this view with bank patents showing a growing customer-orientation along our sample timeline. As a result, the significance of the coefficient for the operations/IT category could reflect the importance for banks of making the general decision to engage in R&D.

4.3 Baseline Results - Local Mortgage Lending

The results so far show that local bank branches of innovative BHCs are able to take in significantly more deposits than branches of non-innovating banks. To answer the question whether these

[13]In fact, banks could profit from the first-mover advantage both *directly* via improved processes and lower costs as well as *indirectly* via signaling their abilities and innovativeness to customers, see also Tufano (1989) who argues that for financial innovation in investment banking, the indirect effect should clearly dominate the direct effect.

liquidity shocks help banks overcome financing frictions and extend their lending, we now analyze the changes in mortgage loan originations. More precisely, we again estimate the IV regressions from Equation (3) where we employ the percentage growth in mortgage loans at the branch-year level as our outcome variable.

[Place Table V about here]

Table V presents the estimation results from the IV panel-regressions together with the results of OLS regressions for our $Patents$, $Financial\ Patents$, as well as $Non-Financial\ Patents$ variables. We find bank innovation to have a significant and positive effect on total mortgage growth. The found statistically significant results are also economically significant. In our baseline OLS regression, a one standard deviation increase in our innovation proxy is associated with a 4.3% (see column (2), $0.2069 * 0.2086$) higher mortgage growth per branch. As with our regressions of banks' growth in deposits, our proxy for $Human\ Capital$ is a strong predictor of BHCs' patenting activities with all IV regressions passing the Kleibergen-Paak tests easily. In column (4), we estimate an OLS regression in which we again split the bank patent variable into financial and non-financial innovations. The results reveal a differential effect of the two patent categories on mortgage growth. Financial patents enter regression (4) with a statistically significant negative coefficient, while non-financial innovations are significantly positively related to local mortgage growth. This finding is in line with our intuition. While financial innovations (that predominantly originate in the investment banking business of a BHC) allow banks to shift their business away from traditional lending, non-financial patents that are usually related to the retail business of a bank enable the BHC to extend its credit supply.

As in our analysis of banks' growth in local deposits, we use the decomposition of our main explanatory variable into the six previously defined categories and estimate regressions in which these categories are used individually (IV) as well as jointly (OLS) to explain the variation in local mortgage growth. The results of these regressions are shown in Table VI.

[Place Table VI about here]

Columns (1) to (6) show the results of the IV regressions with each category taken individually as our main explanatory variable of interest. Similar to the results on banks' local deposit growth that we document in Table IV, all patent types are shown to have a statistically significant and positive effect on mortgage growth in our IV regressions. Nevertheless, as explained earlier, the high correlation between the patent categories impairs to some extent the validity of these regressions. Thus, in column (7), we employ all patent types in one single OLS regression.[14] This time, the back office operations/IT category is the only one that retains its statistical significance. The evidence we find is thus again consistent with the notion that banks traditionally focused their R&D activities on improvements in information technology and internal bank processes.

The findings up to this point suggest that innovations (esp. in the field of information technology) allow innovating banks to take in additional deposits and extend their credit supply compared to non-innovators. Traditionally, studies in the related literature (see, e.g., Berger et al., 2005; Berger and Kim, 2017) have stressed the importance of the local proximity between a bank and its customers for reducing information asymmetries in lending. If new inventions caused innovating banks to experience a liquidity windfall only, we would expect innovating banks to extend their lending only in those areas in which they operate branches (similarly to the findings of Gilje et al., 2016). If, on the other hand, innovations also led to an improvement and competitive advantage in a bank's lending business, information asymmetries could be overcome even without having a local branch presence near prospective borrowers. Following these two competing views, we next test whether bank innovations have a differential effect on mortgage lending conditional of a bank's branch presence in a given county. Here, we follow Gilje et al. (2016) and define local markets as those in which a bank has at least one branch, and reestimate our previous OLS and IV regressions for the subsample of observations in local and non-local markets.

[Place Table VII about here]

The results for both regressions in Table VII are quite similar. Bank innovations have a positive

[14] Note that the results again come with the caveat that we cannot instrument the patent categories if used simultaneously as covariates.

and significant impact on loan mortgage growth regardless of whether a bank operates a branch in a given county, or not. The economic significance of the effects in both subsamples is of the same magnitude as before in our baseline regression. Consequently, we find evidence that is consistent with innovations and technological progress acting as a substitute for local branches as a means to overcome bank-borrower information asymmetries.

4.4 Local Aggregate Effects

Our results so far show a causal effect of innovation at banks on local liquidity inflows and mortgage lending. In line with the hypothesis of banks profiting directly (via improved, more cost-efficient processes) and indirectly (via reputation effects and a better customer outreach) from innovations, we find more innovative banks to take in significantly more deposits and extend their supply of mortgage loans compared to branches of non-innovating banks. While the exogenous propagation of the innovation shock from a distant BHC to its branches helps us identify the positive effect of innovation on bank liquidity and credit supply, it does allow for two explanations for these findings. On the one hand, innovation shocks to bank branches in a given county could help innovative banks to extend payment services and lending to previously underserved customers thus raising the aggregate level of deposits and mortgage loans in that respective county. On the other hand, innovations could simply lead to banks engaging in a Schumpeterian fight for market shares that eventually results in a mere reallocation of the otherwise fixed amount of deposits and loans from innovators to non-innovators.

Consequently, in our next set of analyses, we try to assess the effects of bank innovation on *aggregate* county-level outcomes. The explanatory variable of interest in these regression analyses is the *Share of Innovating Banks* and is estimated by taking the percentage of branches a BHC owns in a given year and county (see also Degryse and Ongena, 2005, 2007; Bircan and De Haas, 2019, for a similar proxies of bank concentration). In Figure 3, we first plot the geographical variation in the *Share of Innovating Banks* across U.S. counties in the years 1998, 2003, 2008, and 2013, respectively.

[Place Figure 3 about here]

Figure 3 highlights several remarkable findings. First, the four subplots show a clear and increasing trend in the market shares of innovative banks across all U.S. counties. Bank innovations trickle down into an increasing number of previously "innovation-free" local bank markets, and the shares of innovative banks keep increasing along our sample timeline. Second, while we do observe some regional clustering of counties with higher shares of innovative banks (esp. in the west, midwest, and certain metropolitan areas), the dispersion of such counties nevertheless appears to be random across the U.S. thus underlining our identification strategy that relates innovations at BHC headquarters to local branch outcomes. This is not surprising as banks' decisions to enter local banking markets were plausibly made before the onset of bank innovations shortly before the millennium. Finally, and in line with our intuition, the share of innovative banks in local markets decreased all across the U.S. during the Financial Crisis with most BHCs presumably cutting down R&D costs, and increased again to the end of our sample period.

Next, we estimate the growth in total deposits, the number of bank branches, as well as mortgage loans per county and year. Moreover, we also estimate the Herfindahl-Hirshman Index (HHI) of bank branches' total deposits to proxy for bank concentration and thus competition of local bank branches. We then regress these aggregate outcomes on the *Share of Innovating Banks*estimate all regressions with time-varying sociodemographic county controls, county, and state*year fixed effects to control for institutions at the state level as well as local demand effects (see also Gilje et al., 2016).

[Place Table VIII about here]

Table VIII presents the results of the regressions at the aggregate county-year level. The evidence presented in columns (1) and (2) shows clearly that the share of innovative bank branches neither affects the total aggregate deposits nor the number of bank branches in a given county. Taken together with the summary statistics given in Table II on the overall growth in deposits for innovating vs. non-innovating banks, our findings thus support the hypothesis that innovation shocks to local bank branches lead to a redistribution rather than an expansion of bank deposits. In essence, we find that innovative banks fight for local customer deposits with branches of non-innovative banks presumably losing to innovators. To give our line of argumentation more credibility, we estimate regressions of the local HHI of bank deposits on the share of innovative bank branches to test whether an increase in the overall innovation in a county's local banks leads to a higher concentration in the local banking market. The baseline test based on our full sample reported in column (4) supports this hypothesis. A higher share of innovative bank branches is associated with a significantly higher local bank branch concentration. We would expect this effect to be particularly pronounced for counties in which few innovative banks compete with large number of non-innovating banks thereby fully exploiting the first-mover advantage. At the same time, the positive relation between bank innovation and bank concentration should decrease as more and more innovative banks compete with each other. To test this conjecture, we build two subsamples that contain only those observations in counties with a low share of innovating banks (column (5); share of innovating banks less than 5%), and counties with a high share of innovating banks (column (6); share of innovating banks higher than 50%), respectively. The results from these regressions support our hypothesis. Bank innovations play a significant role in increasing local bank concentration, but only in the subsample of counties in which innovative banks still only have a small market share.

Lastly, we evaluate the effect of bank innovation in a county on aggregate mortgage loans. As bank innovations seem to lead to a redistribution, and not an expansion of deposits, one could argue that mortgage loans are only redistributed as well from non-innovators to innovators. At the same time, improvements in banks' efficiency could also allow banks to attract more loan applications and loosen their financing constraints thereby leading to an increase in overall mortgage loans. In column (3) of Table VIII, we test this relation. The coefficient on the share of innovative banks in a county now turns out to be statistically significant and positive. The higher the share of innovative banks in a given county, the higher the growth in total mortgage loans in that county. The results in Table VIII thus establish that bank innovations foster local bank concentration and stimulate overall lending.

4.5 Do Branches of Innovative Banks Get More/Better Loan Applications?

Up to this point, our findings indicate that local bank branches extend their credit supply as a result to innovation shocks from their respective holding companies. Taken together with our findings on branches' innovation-induced increase in deposits, these results support the hypothesis that innovations help banks to lift financing constraints and attract new customers when it comes to mortgage lending. Alternatively, the increase in local market power at branches of innovative banks could worsen agency problems and overconfidence on the part of bank managers (see Jensen, 1986; Roll, 1986; Malmendier and Tate, 2005) in turn leading them to accept unprofitable loan applications.[15] To decide which explanation is consistent with our data, we next estimate regressions on outcome variables that are related to the *quality* of granted (and retained) loans.

[Place Table IX about here]

Table IX presents the results of branch-year-level regressions in which we first employ the natural logarithm of the number of loan applications (columns (1) and (2)) and the fraction of granted loans as a percentage of the total number of loan applications (columns (3) and (4)) as dependent variables. Complementing these analyses, in columns (5) and (6), we estimate regressions at the BHC-year-level in which we use the fraction of mortgage loans that were charged off or are delinquent (90 days or more past due or nonaccruing) as our outcome variable of interest. For all regressions, we report IV estimates for the (log) number of patents as well as OLS estimates for regressions in which we split our main variable of interest into financial and non-financial patents. Furthermore, we include our previous sets of covariates and include bank, year (BHC level), and region*year (branch level) fixed effects. The results show clearly that innovations increase the number of loan applications and decrease average acceptance rates. In line with the hypothesis of

[15] Fahlenbrach and Stulz (2011) find little to no evidence for misaligned managerial and shareholders interests to have had a negative influence on bank performance during the financial crisis. Their results at the CEO level, however, might not hold for local bank managers so that we cannot simply rule out agency problems explaining the increase in lending.

innovations enabling banks to attract depositors (and thus new customers) that subsequently apply for mortgage loans. At the same time, and again in line with the idea of innovations improving overall bank efficiency, more innovative banks seem to be more selective in their choice of investment projects with acceptance rates for loan applications decreasing significantly. The results of our regressions of banks' loan quality at the BHC-level in column (5) strongly support this line of reasoning. Bank innovations have a significantly negative effect on banks' charge-off ratios. Again, we find financial and non-financial patents to have a differential effect on our outcome variable. While financial innovations (that are usually not related to the commercial but rather the investment banking business of a BHC) have an increasing influence on loan quality, non-financial patents affect overall loan quality with the expected negative sign. In summary, we find that innovative banks receive more loan applications (as a result of their stronger position in local markets), but also become more selective in their lending with overall loan quality improving as a result of (especially) process innovations.

4.6 Robustness Checks

Table X reports a wide set of robustness tests on the found impact of banks' innovation activities on deposit growth (Panel A) and lending (Panel B). The results are reported in rows and represent IV-estimations using the number of Doctoral Degrees (except in row (1)) as our instrument for banks' innovation. To save space, we only report the coefficient on our main variable of interest in each regressions.

First, we implement our alternative identification strategy as laid out in Equation (6) using the overall leniency of the patent examiner assigned to a bank's patent application as an alternative instrument for bank innovation. As our instrument *Leniency* can only be estimated for banks that have applied for at least one patent during our sample period, we are only able to interpret the results from our second stage as a local treatment effect on the subsample of complying innovating banks. The results of this alternative IV regression, of which the detailed results are given in the Internet Appendix in Table IA.I, show that bank innovation retains its positive and highly significant effect on both banks' deposit growth and mortgage growth.

In row (2) of Table X, we estimate our panel estimations using county-clustered standard errors. The results are similar to those reported in our baseline panel estimations in terms of both statistical and economic magnitude. Next, we reestimate our main regressions using bank and county*year fixed effects (instead of region*year fixed effects) (see Gilje et al., 2016, for a similar approach). Controlling for county*year fixed effects helps us to capture overall local economic conditions affecting deposit-taking and credit demand even better than with our baseline approach (while at the same time driving up the computational cost due to the large number of county*year combinations). Adding county*year fixed effects does not affect our results significantly (see rows (3) in Panels A and B).

Furthermore, in row (4), we test our previously stated hypothesis that the general decision to innovate rather than the degree to which a bank innovates is important to banks. For this, we follow Gaulé (2018) and estimate (otherwise unchanged) regressions in which the endogeneous variable is a dummy variable for having at least one patent instead of the (log) number of patents. Again, we find bank innovations to be positively and significantly related to outcomes at the local branch level. Interestingly, the point estimates on the coefficient of the dummy variable are significantly larger than those from our baseline regression. Thus, an not surprisingly, we again find evidence for the notion that the first patent of a BHC (and more generally the decision to engage in R&D) possesses a considerably higher importance than subsequent ones.

An extensive literature has highlighted the usefulness of a patent's citations to quantify the innovative performance of that respective patent as an alternative innovation proxy (see, e.g., Griliches et al., 1988).[16] For this reason, we use the variable *Citations* (rows (5)), which represents the average number of citations per patent that a BHC applies for in a given year (see also Tian and Wang, 2011). The results of these alternative estimations are presented in detail in the

[16]Extant literature suggests to differentiate between the originality and generality of patents, e.g., by making use of the proxies developed by Trajtenberg et al. (1997) and computed by Hall et al. (2001). In case of our sample, the availability of the data needed to compute these measures ends in 2006. However, the number of patent applications in our sample significantly increases during the mid-2000s. Thus, we refrain from estimating proxies of patent originality and generality in our analyses.

Internet Appendix in Table IA.II. Additionally, to capture the importance of each patent, we follow Tian and Wang (2011) and construct in row (6) our variable *Long-term Citations* by counting the total number of citations each patent receives in subsequent years. Similarly, we construct the variable Short-term Citations in row (7) by counting the total number of citations each patent receives in the first five years after its respective application. Rows (5) through (7) in Table X show that the results from these robustness checks using alternative innovation proxies are similar to those reported in our baseline panel estimations in terms of both statistical and economic magnitude.

Recent research has demonstrated that patent counts do not necessarily capture the importance of a given patent (see, e.g., Hall et al., 2001; Harhoff et al., 1999; Amore et al., 2013). Therefore, in row (8) we complement our previous estimations and construct the variable *Citation-weighted patents* by weighting a bank's number of patents with the number of citations received in the future (see Amore et al., 2013, for a similar approach). This variable gives us a more detailed impression of the success of bank's patenting activities. The coefficient on the proxy for innovation success retains its sign and significance in all regressions.[17]

We also evaluate whether the direction of the effect of bank innovation on both deposit and mortgage growth changes when excluding the financial crisis of 2007-2009 from our sample. They do not, as the results in row (9) still indicate a positive effect of bank innovation on both local deposit growth and lending. Next, it could be argued that the onset of digitalization in the banking sector and the emerging of fintechs after the financial crisis constitutes a structural break in our sample. As a result, our results could only hold for the subsample before the financial crisis when innovations in banking were still rare. Therefore, in row (10), we limit our sample to the time window starting in 2010, i.e., we start our sample at a time when all banks had had ample time to realize the benefits of the internet and digitalization. Though this restriction leads to a large drop in

[17] By using the citation-related proxies for the importance of a bank's innovations, we are also (indirectly) addressing the concern that our results are biased by banks merely acting as nonpracticing entities or so-called "patent trolls" (cf. Appel et al., 2019): First, as the banks in our sample applied for the patents themselves, we can rule out any bias stemming from banks receiving the rights to patents from (former) borrowers, e.g. in case of a borrower's default. Second, if banks only applied for patents to target competitors with infringement claims, we would expect banks' patents to be of subpar quality and our main results to become insignificant when switching to proxies of patent quality. With the mean number of yearly citations of a bank's patents being at 53.31, and given the results in rows (5) to (8) in Table X, we feel confident that can rule out the "patent troll" explanation.

our sample size, we still find a significant positive effect of bank innovation on deposit growth and mortgage growth. Moreover, it could be argued that our results are driven by few sample outliers, especially in New York City. In an additional robustness check, we thus exclude the state of New York, which accounts for both the highest number of innovating BHCs and the highest number of average bank patent applications in our sample. Rows (11) in Panel A and B both show that the exclusion of this state does not affect our main results.

In our main analysis, we explain the positive effect of innovation on deposit taking and lending by stressing the competitive advantage innovations give to the local branches of innovators. In the context of the U.S. banking system, an obvious alternative explanation for such an effect could be the deregulation of the banking sector brought on by the passing of the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994 (IBBEA).[18] As our sample starts in 1997, no bank is directly affected by the IBBEA bank deregulation. However, allowing BHCs to expand across states resulted in increased credit supply in the 1990s, which was associated with higher adoptions of screening and monitoring technologies (see, e.g., Amore et al., 2013). To rule out that our results are driven by differential competitive pressure in some states that had only recently been deregulated at the start of our sample period, we estimate regressions in which we exclude BHCs located in states that were affected by the bank deregulation only after 1990 (i.e., Arkansas, Colorado, Iowa, Minnesota, and New Mexico). As presented in rows (12), adding this restriction does not affect our results significantly.

Finally, as discussed earlier in the description of our identification strategy, the exclusion restriction for our *Human Capital* instrument could be violated if the IV and local branch outcomes are jointly determined by omitted variables.[19] To further rule out such an endogeneity, we exclude the innovating BHCs' headquarter states (rows (13)) and county (rows (14)) in two additional robustness checks.

By doing so, we minimize the probability that branches located in the BHCs' headquarter state

[18]The IBBEA deregulation is probably one of the best-understood exogenous shocks to competition in the U.S. banking system, starting with the results of Jayaratne and Strahan (1996) on the positive effects of finance on economic growth, and continuing with recent studies by, among many others, Cornaggia et al. (2015) and Goetz et al. (2016).

[19]Our second IV, *Leniency*, should of course not suffer from this problem.

or county could benefit disproportionately from the proximity to the BHC, and that local economic conditions drive both the availability of human capital as well as deposit and loan growth. Detailed results of these estimations are presented in Table IA.III in the Internet Appendix. Again, our main findings remain statistically and economically similar to those of our baseline estimations.

5 Conclusion

In this paper, we study the effect of bank innovation on deposit taking and mortgage lending by U.S. banks. Using the number of awarded doctoral degrees in the MSA of a bank's headquarter as well as the leniency of patent examiners as instruments, we find a strong causal effect of innovations by banks on local deposits and lending. Innovation shocks spilling over from holding companies to their local branches cause a redistribution of deposits in a zero sum game at the expense of the branches of local non-innovating competitors, especially when counties are treated for the first time with innovations in banking. Innovative banks then make use of this additional liquidity, as well as the innovations in processes, operations, and online/mobile banking itselves, to expand mortgage lending. However, rather than just taking lending business away from non-innovators, innovating banks also increase aggregate lending which increases with the share of innovative banks that have a branch presence in a contested county. In line with the notion of innovators driving out less innovative, less efficient competitors, banks that innovate are able to attract more loan applications, attract better loans, and thus increase their overall loan performance.

Our paper provides first evidence of an exponentially increasing trend of banks to innovate. We then continue and highlight the beneficial effects of bank innovation on local lending via the local competitive pressure it creates. These results are important for at least two reasons. First, they document the increasing importance of innovations in an industry that was previously void of any technological advances and process innovations. Digitalization and innovation are not just a necessary condition for banks to survive in the direct contest with start-up fintechs and IT companies, but they can produce competitive advantages against traditional rivals in local banking markets (and already have since the early 2000s). Second, our findings provide evidence for a positive first-order effect of innovation on financing (rather than the traditional opposite view that finance helps firms to innovate). Innovations are found to increase bank efficiency and improve loan performance, thereby increasing aggregate mortgage lending and total loan growth. While we do not explicitly study firm lending by banks in our analysis, we see little reason to doubt that the positive effects of bank innovation will not translate into banks' corporate lending. As a result, our paper hints at a new facet of the bank lending channel. Complementing previous work on the effects of credit expansion on economic growth that have used supply-side shocks to banks' liquidity or regulatory interventions for identification, our study is indicative of an additional mechanism in which innovations enable banks to expand their lending not only to mortgage lenders but also firms. We intend to address the implications of bank innovation on the finance-growth nexus in our future work.

Appendix I: Variable definitions and data sources.

The appendix presents definitions for all dependent and independent variables that are used in the empirical study. The distribution of bank branches is retrieved from the FDIC Summary of Deposits database and Patent data are retrieved from the *U.S. Patent and Trademark Office (USPTO)*. The variables in Panel B are retrieved from annual HMDA data. All accounting data are collected in U.S. Dollar.

Variable	Description	
Patent variables		
Patents	Total number of applied (and later granted) patents per year .	USPTO.
Financial Patents	Total number of applied financial (and later granted) patents per year (see Lerner (2002).	USPTO (PAIR).
Non-Financial Patents	Total number of applied non-financial (and later granted) patents per year .	USPTO (PAIR).
ATM	Total number of applied patents related to ATMs/Payment services and accounts per year.	Own calculation.
Online/Mobile Banking	Total number of applied patents related to Online/Mobile Banking services per year.	Own calculation.
Operations/IT	Total number of applied patents related to Operations/IT per year.	Own calculation.
Financial Product Innovations	Total number of applied patents related to Financial Product Innovations per year.	Own calculation.
Credit Risk Processing	Total number of applied patents related to Credit Risk Processing and Loan Processing per year.	Own calculation.
Portfolio Selection and Trading	Total number of applied patents related to Portfolio Selection and Trading per year.	Own calculation.
Examiner Leniency	Difference between the leniency of the patents' examiner and the average leniency of all examiners facing application from the same technological area i.e. art unit u in year t.	USPTO.
Citations	Total number of nonself citations a patent receives in the application year.	Own calculation.
Long-term Citations	Total number of number of nonself citations a patent receives in all subsequent years.	Own calculation.
Short-term Citations	Total number of nonself citations a patent receives in the first five years after patent application.	Own calculation.
Citation-weighted patents	Total number of a bank's number of patents weighted by future citations received.	Own calculation.

Appendix II: Variable definitions and data sources. (continued)

Variable	Description	
BHC variables		
C&I Loans/Total Assets	Commercial and industrial loans per total assets.	Call Reports.
Consumer Loans/Total Assets	Total consumer loans divided by total assets.	Call Reports.
Total Loans/ Total Assets	Total deposits divided by total assets.	Call Reports.
Total Assets	Natural logarithm of a bank's total assets at fiscal year end.	Call Reports.
ROA	Return on Assets defined as net income over total assets.	Call Reports.
Noninterest Income/Total Income	Noninterest income divided by total income.	Call Reports.
Total Deposit/Total Assets	Total deposits divided by total assets.	Call Reports.
Total Deposits/ Total Assets	Total deposits divided by total assets.	Call Reports.
Non-performing Loans	Non-performing loans divided by total loans.	Call Reports.
Interest Expenses/Deposits	Interest expenses on deposits divided by total deposits.	Call Reports.
Deposit Growth	Percentage change in BHC's deposits per year.	Call Reports.
Total Loans Growth	Percentage change in BHC's total loans per year.	Call Reports.
Loan application variables		
Mortgage Growth	Percentage change in banks' mortgage growth level per year.	HMDA.
Borrower Income	Average borrower's income per bank and year.	HMDA.
Loan size to income	Average loan amount to borrowers' income ratio per bank and year.	HMDA.
Women applicants	Percentage of women applicants per bank and year.	HMDA.
Minority applicants	Percentage of minority applicants per bank and year.	HMDA.
County and MSA variables		
Minorities in county	Percentage of minorities per county and per year .	NBER Census data.
Income per capita per county	Average income per capita in a county per year .	NBER Census data.
No of Doctoral degrees	Average number of awarded doctoral degrees (all sciences) per MSA and per year .	NSF (HERD).

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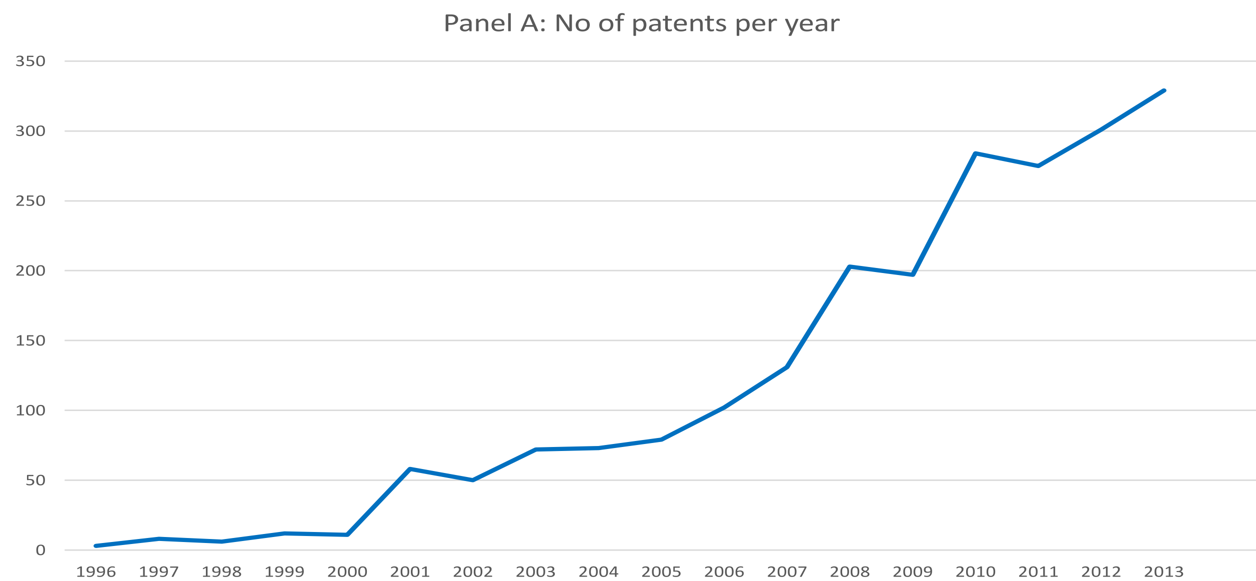
Figure 1: No of patents per year, 1996-2013.

This figure presents the time evolution of the number of applied (and later granted) patents between 1996 and 2013 at U.S. bank holding companies. While Panel A shows the total number of all applied and granted patents, Panel B plots patents categorized as financial and non-financial patents per year following the categorization by Lerner (2002). Patent data are retrieved from the *U.S. Patent and Trademark Office (USPTO)*.



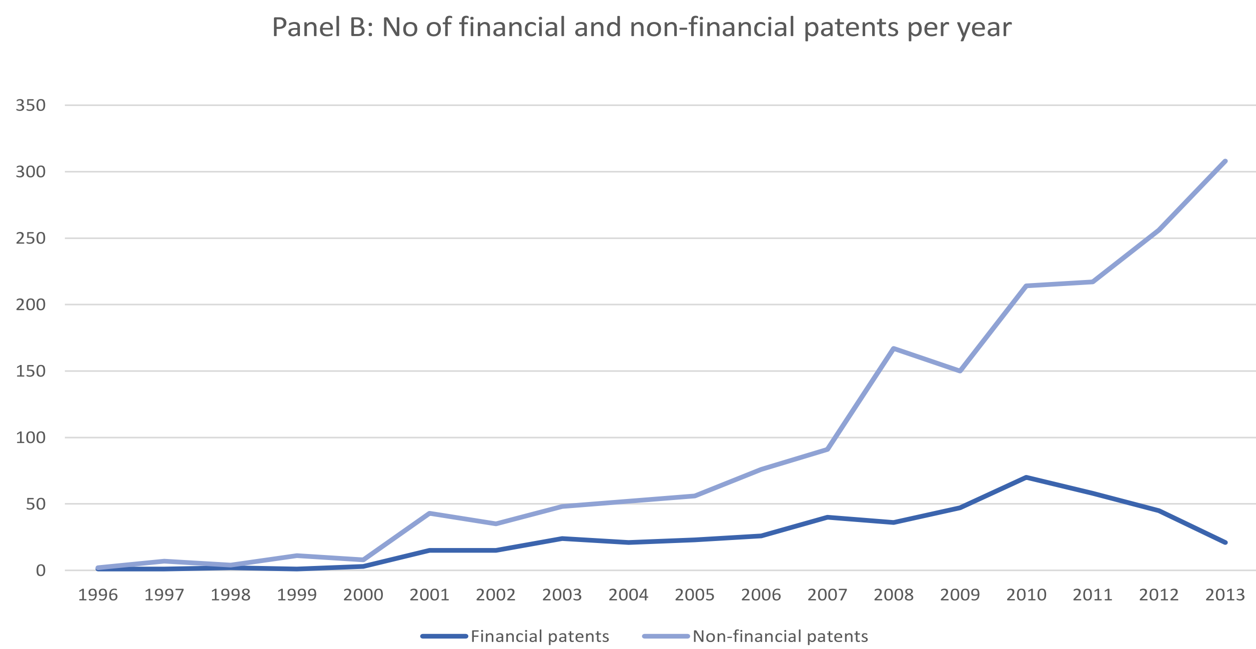


Figure 2: No of patents per category and year, 1996-2013.

The figure plots the time evolution of the number of BHCs' applied (and later granted) patents between 1996 and 2013 classified into six patent categories. Patent data are retrieved from the *U.S. Patent and Trademark Office (USPTO)*.

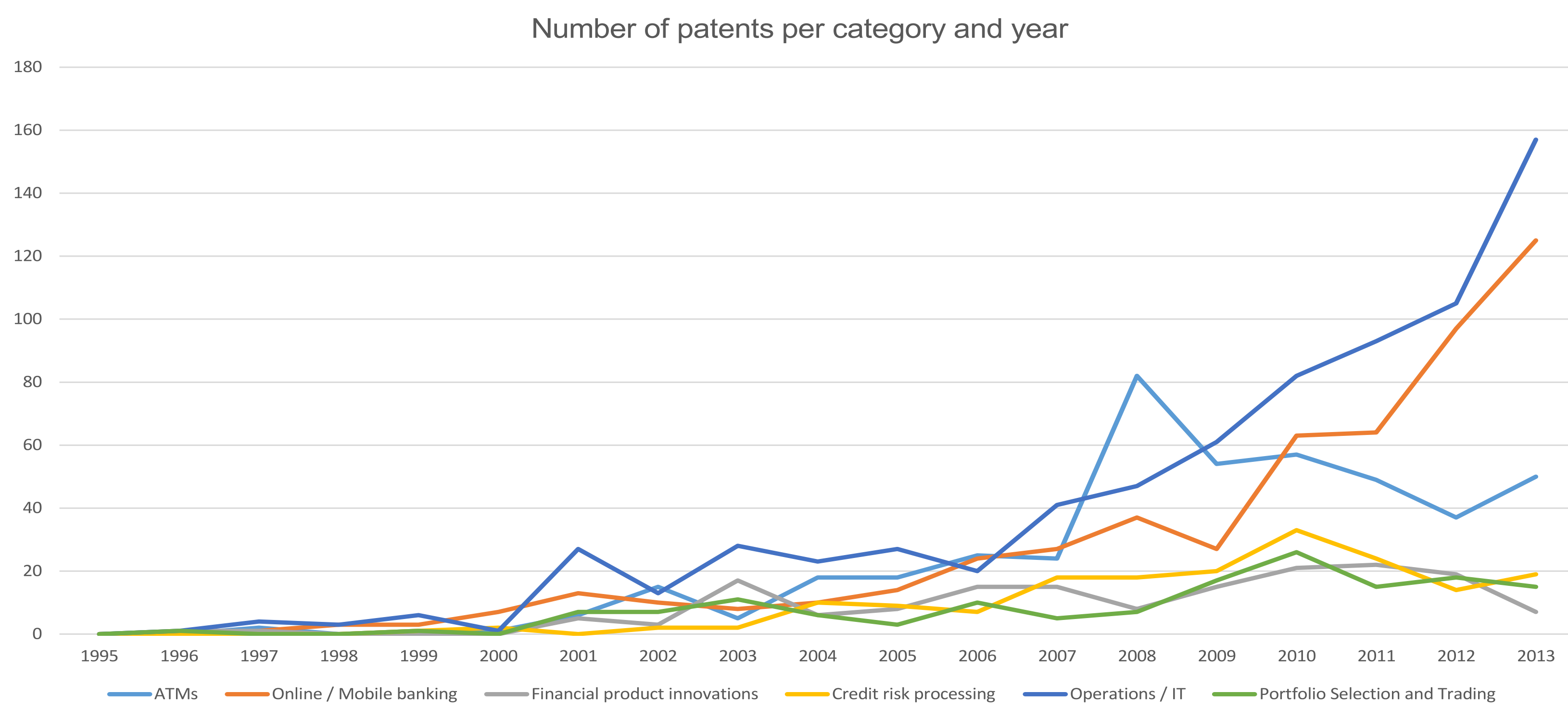


Figure 3: Share of innovative banks per county (as a percentage of branches), 1998/2003/2008/2013.

The figure plots the share of innovative banks at the county level in the years 1998, 2003, 2008, and 2013, respectively. The share of innovative banks in a given county is calculated as the number of branches operated by BHCs with at least one granted patent in the respective year given as a percentage of all branches operated in that county. Patent data are retrieved from the *U.S. Patent and Trademark Office (USPTO)*.

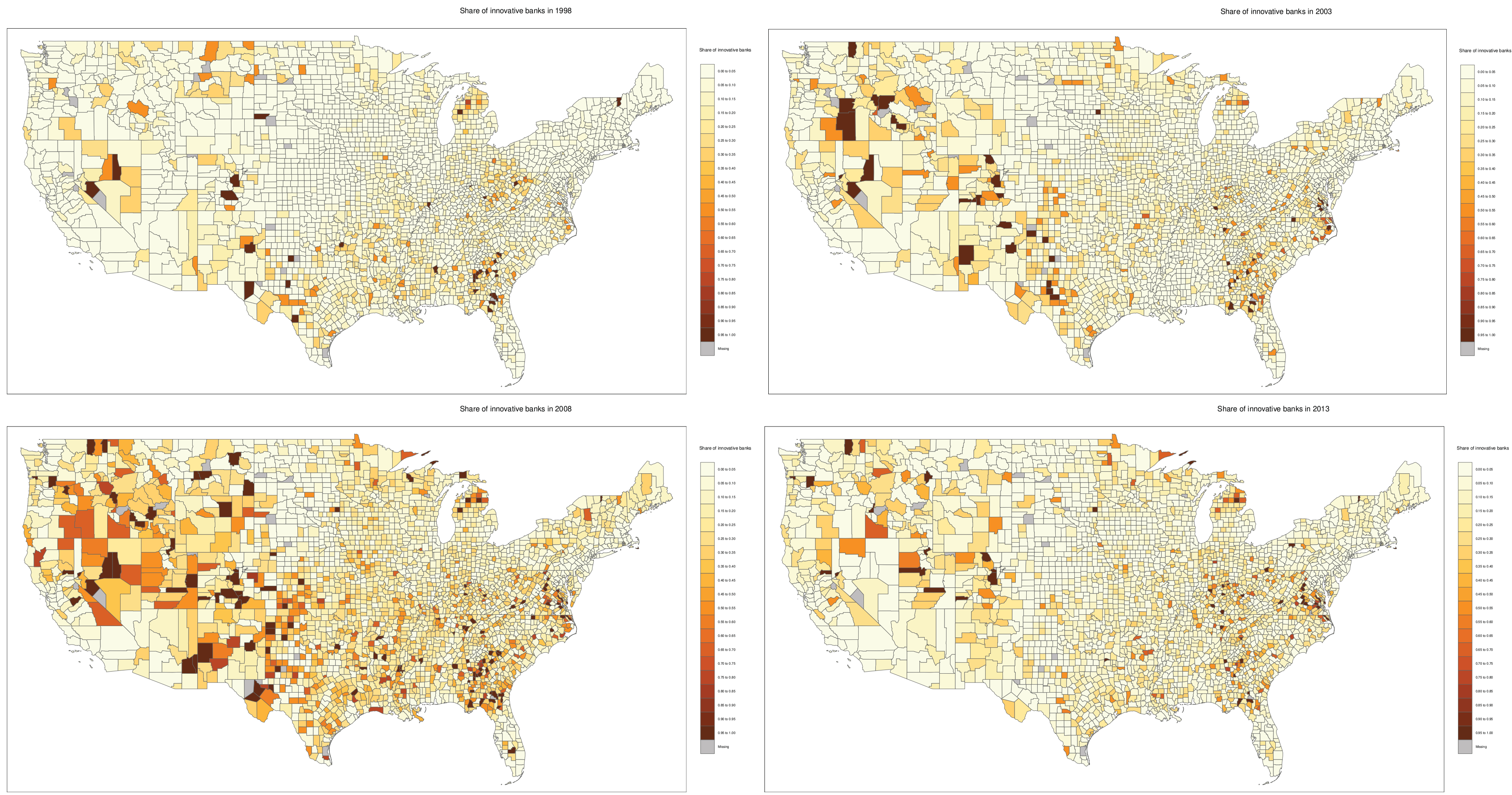


Table I: Summary statistics

This table provides summary statistics for a panel of U.S. banks from 1997 to 2014. In Panel A, observations are provided at the patent-year level, in Panel B at the BHC-year level, in Panel C at the bank-branch-year level and in Panel D and E at the county-year and MSA-year level, respectively. The sample is constructed from all listed Bank Holding Companies from which we retrieve financial statement data from year-end Call Reports. The distribution of bank branches is retrieved from the FDIC Summary of Deposits database and Patent data are retrieved from the *U.S. Patent and Trademark Office (USPTO)*. Lending variables in Panel C are retrieved from annual HMDA data. All accounting data are collected in U.S. Dollar. The variable definitions and data sources are given in Appendix I.

	Innovating banks		**Non-innovating banks**	
No of bank-branch-years	95,810		354,553	
No of BHC-county-years	40,747		48,231	
	Mean	SD	Mean	SD
Panel A: Innovation proxies (BHC-year level)				
Patents	22.141	40.276		
Financial Patents	4.515	6.287		
Non-Financial Patents	17.626	36.110		
ATM	4.404	8.744		
Online/Mobile Banking	5.212	12.142		
Operations/IT	7.323	15.904		
Financial Product Innovations	1.606	2.562		
Credit Risk Processing	1.747	3.233		
Portfolio Selection and Trading	0.137	0.146		
Examiner Leniency	0.137	0.146		
Citations	53.313	95.327		
Long-Term Citations	387.212	611.040		
Short-Term Citations	290.788	466.439		
Citation-Weighted Patents	0.167	0.241		
Panel B: BHC-year characteristics				
C&I Loans/Total Assets	0.091	0.070	0.108	0.069
Consumer Loans/Total Assets	0.087	0.087	0.056	0.061
Total Loans/ Total Assets	0.480	0.198	0.668	0.124
Total Assets (in $m)	686.906	760.366	5.216	52.523
ROA	0.009	0.006	0.009	0.010
Noninterest Income/Total Income	0.418	0.174	0.145	0.097
Total Deposits/ Total Assets	0.532	0.186	0.802	0.087
Non-Performing Loans	0.021	0.020	0.011	0.016
Charge-Off Ratio	0.011	0.012	0.005	0.011
Branch Growth	0.125	0.637	0.056	0.175
Interest Expenses/Deposits	0.032	0.024	0.027	0.016
Deposit Growth	0.122	0.149	0.092	0.131
Total Loans Growth	0.095	0.165	0.098	0.142
Panel C: Bank-branch-year characteristics				
Mortgage Growth	0.012	1.162	-0.074	1.514
Deposit Growth	0.043	0.515	0.081	0.596
Borrower Income	93.387	132.868	104.004	182.500
Loan Size to Income	1.766	1.827	1.599	2.019
Women Applicants	0.399	2.820	0.209	0.250
Minorities Applicants	0.147	1.701	0.065	0.174
Loan Acceptance Rate	0.445	0.302	0.626	0.276
No of Loan Applications	262.640	1204.205	98.962	545.449
Panel D: County characteristics				
Minorities in County	0.143	0.157	0.140	0.160
Income per Capita per County	30.254	9.509	29.531	9.522
Panel E: MSA characteristics				
Human Capital	1875.293	2280.930	211.469	623.660

Table II: Impact of banks' innovation-level on BHC's characteristics

This table reports bank-year panel estimations of BHC's growth in total loans, deposit growth, percentage change in the number of total branches, price of deposits (total interest expense on deposits/deposits) and ROA on bank innovation. The sample is constructed from all BHCs from which we retrieve financial statement data from year-end Call Reports. Patent data are retrieved from the *U.S. Patent and Trademark Office (USPTO)*. All accounting data are collected in U.S. Dollar. The variable definitions and data sources are given in Appendix I. P-values are given in parentheses and ***, **, * indicate an estimate that is statistically significantly different from zero at the 1%, 5%, and 10% level, respectively.

	Total Loan Growth	Deposit Growth	Branch Growth	Interest Expenses/ Deposits	ROA
	(1)	(2)	(3)	(4)	(5)
Patents	0.0347*	0.0366**	0.0642*	-0.0036***	0.0008
	(0.083)	(0.047)	(0.066)	(0.002)	(0.193)
Total Assets	-0.1407***	-0.1586***	-0.0391***	0.0030***	-0.0023***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Noninterest Income/Total Income	0.0611**	0.0793***	0.0405	-0.0069***	0.0169***
	(0.043)	(0.002)	(0.402)	(0.000)	(0.000)
Nonperforming Loans	-2.0046***	-1.3826***	-0.5188***	0.0072	-0.2121***
	(0.000)	(0.000)	(0.004)	(0.357)	(0.000)
Consumer Loans/Total Assets	-0.0788	-0.0263	0.0507	-0.0054*	0.0010
	(0.183)	(0.613)	(0.657)	(0.067)	(0.866)
C&I Loans /Total Assets	0.1857***	0.1786***	0.0983	-0.0107***	-0.0081*
	(0.000)	(0.000)	(0.115)	(0.000)	(0.063)
Total Loans/Total Assets	-0.2890***	0.2235***	-0.0198	0.0012	0.0014
	(0.000)	(0.000)	(0.528)	(0.417)	(0.548)
Total Deposits/Total Assets	-0.0632*	-0.6245***	-0.0882	-0.0466***	-0.0072*
	(0.082)	(0.000)	(0.108)	(0.000)	(0.089)
ROA	1.9138***	1.7429***	1.5054*	-0.0889***	
	(0.000)	(0.000)	(0.052)	(0.000)	
Bank fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	15,372	15,372	15,633	15,311	15,221
R^2	0.4528	0.4108	0.2473	0.8669	0.5146

Table III: Effect of innovation on deposit growth

This table provides panel-estimations of banks' deposit growth by bank-county-year on banks' innovation from 1997 to 2014. The sample is constructed from all BHCs from which we retrieve financial statement data from year-end Call Reports. Patent data are retrieved from the *U.S. Patent and Trademark Office (USPTO)*. To identify financial patents, we follow Lerner (2002). Lender controls are retrieved from the Call Reports from the prior year. We also control for county-characteristics, i.e., percent minorities per county and average income per capita in a county. All regressions include both US-Region*year fixed effects as well as bank fixed effects (see Acharya et al. (2012)). The U.S. Census Bureau distinguishes four U.S. regions: Northeast, South, Midwest, and West. All accounting data are collected in U.S. Dollar. The variable definitions and data sources are given in Appendix I. P-values are given in parentheses and ***, **, * indicate an estimate that is statistically significantly different from zero at the 1%, 5%, and 10% level, respectively.

Dependent variable: Deposit Growth				
	First Stage	OLS	IV	OLS
	(1)	(2)	(3)	(4)
Patents		0.0323***	0.0375***	
		(0.000)	(0.000)	
Financial Patents				0.0120*
				(0.076)
Non-Financial Patents				0.0249***
				(0.000)
No of Doctoral degrees	0.3096***			
	(0.000)			
C&I loans/Total Assets	-1.8789***	-0.0316	-0.0168	-0.0369
	(0.000)	(0.665)	(0.827)	(0.615)
Consumer Loans/Total Assets	5.2035***	-0.1522**	-0.1844**	-0.1533**
	(0.000)	(0.047)	(0.038)	(0.047)
Total Loans/ Total Assets	-1.6933***	-0.0307	-0.0206	-0.0329
	(0.000)	(0.482)	(0.655)	(0.448)
Minorities in county	-0.2269***	0.0921**	0.0939**	0.0916**
	(0.000)	(0.039)	(0.037)	(0.040)
Income per capita per county	-0.0024***	-0.0019***	-0.0019***	-0.0019***
	(0.000)	(0.005)	(0.006)	(0.005)
Total Assets	0.1637***	-0.0062	-0.0073	-0.0065
	(0.000)	(0.386)	(0.320)	(0.363)
ROA	1.8116***	0.5553**	0.5544**	0.5646***
	(0.000)	(0.012)	(0.012)	(0.010)
Noninterest Income/Total Income	0.0755***	0.1617***	0.1598***	0.1643***
	(0.009)	(0.000)	(0.000)	(0.000)
Total Deposits/ Total Assets	-2.0435***	0.1118**	0.1243**	0.1215**
	(0.000)	(0.022)	(0.014)	(0.016)
Non-performing Loans	7.7727***	-0.1928	-0.2350	-0.1814
	(0.000)	(0.188)	(0.134)	(0.208)
Kleibergen-Paap Underidentification test			5839.43	
Bank fixed effects	Yes	Yes	Yes	Yes
Region*year fixed effects	Yes	Yes	Yes	Yes
Observations	148,226	148,226	148,226	148,226
R^2	0.9014	0.2079	0.2075	0.2079

Table IV: Patent categories on deposit growth

This table provides panel-estimations of banks' deposit growth by bank-county-year on different banks' patent categories from 1997 to 2014. The sample is constructed using innovating BHCs from which we retrieve financial statement data from year-end Call Reports. Patent data are retrieved from the *U.S. Patent and Trademark Office (USPTO)*. Regressions include lender control variables that are retrieved from the Call Reports from the prior year. We also control for county-characteristics, i.e., percent minorities per county and average income per capita in a county. All regressions also include US-Region*year fixed effects (see Acharya et al. (2012)). The U.S. Census Bureau distinguishes four U.S. regions: Northeast, South, Midwest, and West. All accounting data are collected in U.S. Dollar. The variable definitions and data sources are given in Appendix I. P-values are given in parentheses and ***, **, * indicate an estimate that is statistically significantly different from zero at the 1%, 5%, and 10% level, respectively.

Dependent Variable: Deposit Growth							
	IV (1)	IV (2)	IV (3)	IV (4)	IV (5)	IV (6)	OLS (7)
ATM	0.0611***						-0.0079
	(0.000)						(0.508)
Online Banking/Mobile		0.0556***					0.0083
		(0.000)					(0.190)
Operations/IT			0.0453***				0.0276***
			(0.000)				(0.000)
Financial Innovation Patents				0.1747***			0.0022
				(0.000)			(0.852)
Credit Processing					0.1166***		0.0232**
					(0.000)		(0.021)
Portfolio Selection and Trading						0.1161***	-0.0128
						(0.000)	(0.150)
County controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Underidentification test	7133.25	6786.74	7260.70	3747.22	3024.55	5971.17	
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region*year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	148,226	148,226	148,226	148,226	148,226	148,226	148,226
R^2							0.2079

Table V: Effect of innovation on mortgage growth

This table provides panel-estimations of banks' mortgage growth by bank-county-year on banks' innovation from 1997 to 2014. The sample is constructed from all BHCs from which we retrieve financial statement data from year-end Call Reports. Patent data are retrieved from the *U.S. Patent and Trademark Office (USPTO)*. To identify financial patents, we follow Lerner (2002). Regressions include both lender and borrower control (not reported) variables. Lender controls are retrieved from the Call Reports from the prior year. Borrower controls are retrieved from the HMDA database and display average borrower income, loan size-to-income ratio, percent women applicants, and percent minority applicants. We also control for county-characteristics, i.e., percent minorities per county and average income per capita in a county. All regressions include both US-Region*year fixed effects as well as bank fixed effects (see Acharya et al. (2012)). The U.S. Census Bureau distinguishes four U.S. regions: Northeast, South, Midwest, and West. All accounting data are collected in U.S. Dollar. The variable definitions and data sources are given in Appendix I. P-values are given in parentheses and ***, **, * indicate an estimate that is statistically significantly different from zero at the 1%, 5%, and 10% level, respectively.

Dependent variable: Mortgage Growth				
	First Stage	OLS	IV	OLS
	(1)	(2)	(3)	(4)
Patents		0.2086***	0.5415***	
		(0.000)	(0.000)	
Financial Patents				-0.2334***
				(0.000)
Non-Financial Patents				0.3452***
				(0.000)
No of Doctoral degrees	0.2008***			
	(0.000)			
C&I loans/Total Assets	-0.7739***	-0.2459*	0.2056	-0.0744
	(0.000)	(0.062)	(0.128)	(0.571)
Consumer Loans/Total Assets	5.5166***	0.8513***	-1.0904***	1.0855***
	(0.000)	(0.000)	(0.000)	(0.000)
Total Loans/ Total Assets	-2.7499***	0.5277***	1.4602***	0.2996***
	(0.000)	(0.000)	(0.000)	(0.000)
Minorities in county	-0.3489***	0.5259***	0.6776***	0.5026***
	(0.000)	(0.000)	(0.000)	(0.000)
Income per capita per county	-0.0021***	-0.0022	-0.0013	-0.0028*
	(0.000)	(0.153)	(0.396)	(0.070)
Total Assets	0.3379***	-0.0437**	-0.1580***	0.0082
	(0.000)	(0.018)	(0.000)	(0.658)
ROA	3.8038***	3.8039***	3.1299***	3.3004***
	(0.000)	(0.000)	(0.000)	(0.000)
Noninterest Income/Total Income	0.1704***	0.4474***	0.3667***	0.4034***
	(0.000)	(0.000)	(0.000)	(0.000)
Total Deposits/ Total Assets	-0.7851***	1.0559***	1.2977***	0.7602***
	(0.000)	(0.000)	(0.000)	(0.000)
Non-performing Loans	6.3595***	0.4679	-1.5735***	0.3261
	(0.000)	(0.149)	(0.000)	(0.311)
Borrower controls	Yes	Yes	Yes	Yes
Kleibergen-Paap Underidentification test			6310.21	
Bank fixed effects	Yes	Yes	Yes	Yes
Region*year fixed effects	Yes	Yes	Yes	Yes
Observations	450,363	450,363	450,363	450,363
R^2	0.9316	0.3964	0.3944	0.3977

Table VI: Patent categories on mortgage growth

This table provides panel-estimations of banks' mortgage growth by bank-county-year on banks' innovation from 1997 to 2014. The sample is constructed using innovating BHCs from which we retrieve financial statement data from year-end Call Reports. Patent data are retrieved from the *U.S. Patent and Trademark Office (USPTO)*. Regressions include lender control variables that are retrieved from the Call Reports from the prior year. We also control for county-characteristics, i.e., percent minorities per county and average income per capita in a county. All regressions also include US-Region*year fixed effects (see Acharya et al. (2012)). The U.S. Census Bureau distinguishes four U.S. regions: Northeast, South, Midwest, and West. All accounting data are collected in U.S. Dollar. The variable definitions and data sources are given in Appendix I. P-values are given in parentheses and ***, **, * indicate an estimate that is statistically significantly different from zero at the 1%, 5%, and 10% level, respectively.

Dependent Variable: Mortgage Growth							
	IV (1)	IV (2)	IV (3)	IV (4)	IV (5)	IV (6)	OLS (7)
ATM	1.3343*** (0.000)						0.1338 (0.000)
Online Banking/Mobile		1.2277*** (0.000)					0.0638 (0.000)
Operations/IT			0.6388*** (0.000)				0.1902*** (0.000)
Financial Innovation Patents				2.1652*** (0.000)			-0.2413 (0.000)
Credit Processing					2.8182*** (0.000)		-0.0931 (0.000)
Portfolio Selection and Trading						1.4883*** (0.000)	-0.0384 (0.000)
County controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Underidentification test	3320.24	5210.40	9587.70	3190.97	1402.71	6728.88	
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region*year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	450,363	450,363	450,363	450,363	450,363	450,363	450,363
R^2							0.3974

Table VII: The effect of bank innovation on local and non-local lending

This table provides panel-estimations of banks' mortgage growth by bank-county-year on banks' innovation from 1997 to 2014 for local and non-local markets. We follow Gilje et al. (2016) and define local markets as those in which a bank has at least one branch. The sample is constructed from all BHC from which we retrieve financial statement data from year-end Call Reports. Patent data are retrieved from the *U.S. Patent and Trademark Office (USPTO)*. Regressions include both lender and borrower control variables (not reported). Lender controls are retrieved from the Call Reports from the prior year, while borrower controls are retrieved from the HMDA database and display average borrower income, loan size-to-income ratio, percent women applicants, and percent minority applicants. We also control for county-characteristics, i.e., percent minorities per county and average income per capita in a county. All regressions also include US-Region*year fixed effects (see Acharya et al. (2012)). The U.S. Census Bureau distinguishes four U.S. regions: Northeast, South, Midwest, and West. All accounting data are collected in U.S. Dollar. The variable definitions and data sources are given in Appendix I. P-values are given in parentheses and ***, **, * indicate an estimate that is statistically significantly different from zero at the 1%, 5%, and 10% level, respectively.

	Local			Non-local		
	First Stage	OLS	IV	First Stage	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Patents		0.2329***	0.5072***		0.2154***	0.5692***
		(0.000)	(0.000)		(0.000)	(0.000)
No of Doctoral degrees	0.1891***			0.2016***		
	(0.000)			(0.000)		
C&I loans/Total Assets	-0.6887***	0.3895	0.7464***	-0.8162***	-0.3857**	0.0856
	(0.000)	(0.138)	(0.005)	(0.000)	(0.018)	(0.610)
Consumer Loans/Total Assets	6.5566***	1.3198***	-0.5578	4.9444***	0.7840***	-1.0748***
	(0.000)	(0.000)	(0.207)	(0.000)	(0.000)	(0.000)
Total Loans/ Total Assets	-2.8906***	0.9444***	1.7461***	-2.5239***	0.3895***	1.3033***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Minorities in county	-0.2300***	0.7300***	0.8227***	-0.3793***	0.3784***	0.5496***
	(0.009)	(0.000)	(0.000)	(0.000)	(0.007)	(0.000)
Income per capita per county	-0.0034**	-0.0051	-0.0038	-0.0015**	-0.0006	0.0000
	(0.025)	(0.116)	(0.241)	(0.032)	(0.771)	(0.993)
Total Assets	0.3180***	-0.0480	-0.1331***	0.3132***	-0.0470**	-0.1602***
	(0.000)	(0.191)	(0.002)	(0.000)	(0.039)	(0.000)
ROA	2.4991***	0.7482	0.5552	3.7644***	4.7390***	3.9436***
	(0.000)	(0.331)	(0.470)	(0.000)	(0.000)	(0.000)
Noninterest Income/Total Income	0.1759***	0.8440***	0.7762***	0.1575***	0.2993***	0.2192***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)
Total Deposits/ Total Assets	-0.9217***	1.2903***	1.5211***	-0.5775***	1.0026***	1.1866***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Nonperforming Loans	5.8878***	-2.5771***	-4.1913***	6.2964***	1.3603***	-0.7696*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.091)
Borrower controls	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Underidentification test			1440.06			4433.56
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Region*year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	85,952	85,952	85,952	364,411	364,411	364,411
R^2	0.9204	0.4041		0.9428	0.4274	

Table VIII: Effect of bank innovation on county-level aggregate deposits, lending, and bank competition

This tables provides panel-estimations of aggregate deposit growth (column (1)), branch growth (column (2)), and mortgage growth (column (3)) on the share of branches of innovating banks in a county relative to all bank branches in the respective county from 1997 to 2014. Columns (4) to (6) present panel-estimations of the Herfindahl-Hirshman Index (HHI) of bank branches' total deposits as a proxy for bank concentration on the share of innovative bank branches in a given county. While column (4) shows the results of this regression for our full sample, columns (5) and (6) show the results of regressions based on two subsamples that contain only observations in counties with a low share of innovating banks (column (5); share of innovating banks less than 5%), and counties with a high share of innovating banks (column (6); share of innovating banks higher than 50%), respectively. We use both year*state fixed effects and county fixed effects and further include county controls. P-values are given in parentheses and ***, **, * indicate an estimate that is statistically significantly different from zero at the 1%, 5%, and 10% level, respectively.

	Fullsample			Fullsample	Subsample Low Share	Subsample High Share
	Deposit Growth	Branch Growth	Mortgage Growth	HHI	HHI	HHI
	(1)	(2)	(3)	(4)	(5)	(6)
Share of innovating banks	0.0035	0.0027	4.2876**	0.0194***	0.2503***	-0.2228
	(0.798)	(0.784)	(0.013)	(0.004)	(0.000)	(0.387)
County controls	Yes	Yes	Yes	Yes	Yes	Yes
State*year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	55,010	55,451	52,154	55,451	43,138	250
R^2	0.1424	0.1328	0.3763	0.9362	0.9346	0.9785

Table IX: The effect of bank innovation on loan quality

Columns (1) and (2) provide panel-estimations of the natural logarithm of the number of loan applications per bank 1997 to 2014. Columns (3) and (4) provide panel-estimations of banks' loan acceptance rate on banks' innovation from 1997 to 2014. Columns (5) and (6) report bank-year panel estimations of BHC's charge-off ratio on bank innovation. The sample is constructed from all BHC from which we retrieve financial statement data from year-end Call Reports. Patent data are retrieved from the *U.S. Patent and Trademark Office (USPTO)*. To identify financial patents, we follow Lerner (2002). Regressions include both lender and borrower control (not reported) variables. Lender controls are retrieved from the Call Reports from the prior year. Borrower controls (in column (1) to (6) are retrieved from the HMDA database and display average borrower income, loan size-to-income ratio, percent women applicants, percent minority applicants. Regressions (1) to (6) include both US-Region*year fixed effects as well as bank fixed effects (see Acharya et al. (2012)). The U.S. Census Bureau distinguishes four U.S. regions: Northeast, South, Midwest, and West. Estimations (4) to (6) include both year and bank fixed effects. All accounting data are collected in U.S. Dollar. The variable definitions and data sources are given in Appendix I. P-values are given in parentheses and ***, **, * indicate an estimate that is statistically significantly different from zero at the 1%, 5%, and 10% level, respectively.

	No of Loan Applications		Loan Acceptance Rate		Charge-Off Ratio	
	IV	OLS	IV	OLS	IV	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
Patents	0.3289***		-0.0921***		-0.0179**	
	(0.000)		(0.000)		(0.038)	
Financial Patents		0.0215***		-0.0265***		0.0025***
		(0.000)		(0.000)		(0.007)
Non-Financial Patents		0.2119***		-0.0072***		-0.0028***
		(0.000)		(0.000)		(0.000)
C&I loans/Total Assets	0.7839***	0.6340***	-0.0697***	0.0373**	-0.0028	-0.0012
	(0.000)	(0.000)	(0.000)	(0.032)	(0.266)	(0.629)
Consumer Loans/Total Assets	0.2287*	0.7798***	0.6729***	0.2956***	0.0467	0.0426***
	(0.073)	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)
Total Loans/ Total Assets	0.9482***	0.6499***	-0.1489***	0.0238**	0.0057***	0.0079***
	(0.000)	(0.000)	(0.000)	(0.011)	(0.008)	(0.000)
Total Assets	0.4086***	0.4443***	0.0181***	-0.0013	0.0027***	0.0022***
	(0.000)	(0.000)	(0.000)	(0.547)	(0.000)	(0.000)
ROA	5.4053***	5.6570***	-0.0562	-0.2641***	-0.1722***	-0.1709***
	(0.000)	(0.000)	(0.354)	(0.000)	(0.002)	(0.002)
Noninterest Income/Total Income	0.7020***	0.7291***	-0.2198***	-0.2415***	-0.0007	-0.0017
	(0.000)	(0.000)	(0.000)	(0.000)	(0.815)	(0.563)
Total Deposits/ Total Assets	-0.2913***	-0.3523***	-0.0134	0.0204**	-0.0053**	-0.0047**
	(0.000)	(0.000)	(0.184)	(0.036)	(0.026)	(0.048)
Non-Performing Loans	-0.3756*	0.1858	0.1061**	-0.3634***	0.2314***	0.2247***
	(0.091)	(0.325)	(0.035)	(0.000)	(0.000)	(0.000)
Kleibergen-Paap Underidentification test	7434.50		7434.49		9.63	
County controls	Yes	Yes	Yes	Yes	No	No
Borrower controls	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	No	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Region*year fixed effects	Yes	Yes	Yes	Yes	No	No
Observations	425,213	425,213	425,213	425,213	12,844	12,844
R^2		0.8794		0.6727		0.6856

Table X: Robustness checks.

This table provides robustness checks controlling for different effects on Deposit Growth (Panel A) and Mortgage Growth (Panel B). Each estimation includes year*US-Region fixed effects, bank and county controls and in Panel B also borrower controls. Coefficients are unreported in order to save space. However, some robustness checks are presented in the Internet Appendix. Row (1) uses Examiner Leniency as an instrument for the number of patents granted to banks. Row (2) considers clustered county standard errors. In row (3), we apply county*year fixed effects instead of US-Region*year fixed effects. In row (4) we use a dummy variable taking the value of one, if the bank applied for a patent and zero otherwise. In row (5) we use the variable Citations, which represents the total number of citations per patent that a BHC applies for in a given year. In row (6), we use the definition of Tian and Wang (2011) and count the number of citations each patent receives in subsequent years. Similarly, we control for a the sum of citations each patent receives after the first five years after application (row (7)). Additionally, we follow Amore et al. (2013) and consider in row (8) a bank's number of patents weighted by future citations received. Row (9) excludes the financial crisis from 2007 to 2009. In row (10), we use a time window starting in 2010. Row (11) excludes state New York as the state with the highest number of average bank patent applications. In row (13) and (14) we exclude the BHC's state or county headquarter, respectively. The variable definitions and data sources are given in Appendix I. P-values are given in parentheses and ***, **, * indicate an estimate that is statistically significantly different from zero at the 1%, 5%, and 10% level, respectively.

Panel A: Dependent variable: Deposit Growth				
		Proxy Innovation coefficient	p-value	Number of obs.
(1)	Examiner Leniency	0.1614 *	(0.065)	14,897
(2)	Clustered County SE	0.0358 ***	(0.000)	148,226
(3)	County* time FE	0.0440 ***	(0.000)	148,226
(4)	Innovation Dummy	0.1847 ***	(0.000)	148,226
(5)	Citations in year t	0.0351 ***	(0.000)	148,226
(6)	Long-term Citations	0.0253 ***	(0.000)	148,226
(7)	Short-term Citations	0.0257 ***	(0.000)	148,226
(8)	Citation-weighted patents	1.6090 ***	(0.000)	148,226
(9)	Excluding financial crisis	0.0520 ***	(0.000)	118,460
(10)	Time window starting in 2010	0.3512 ***	(0.000)	36,732
(11)	Excluding State New York	0.0362 ***	(0.000)	140,917
(12)	Excluding states deregulated after 1990	0.0623 ***	(0.000)	122,753
(13)	Excluding innovating BHC's state headquarter	0.0410 ***	(0.000)	117,609
(14)	Excluding innovating BHC's county headquarter	0.0365 ***	(0.000)	139,660
Panel B: Dependent variable: Mortgage Growth				
(1)	Examiner Leniency	0.9989 ***	(0.000)	74,764
(2)	Clustered County SE	0.5415 ***	(0.000)	450,363
(3)	County* time FE	0.4924 ***	(0.000)	450,363
(4)	Innovation Dummy	2.0001 ***	(0.000)	450,363
(5)	Citations in year t	0.4778 ***	(0.000)	450,363
(6)	Long-term Citations	0.2796 ***	(0.000)	450,363
(7)	Short-term Citations	0.2930 ***	(0.000)	450,363
(8)	Citation-weighted patents	28.5144***	(0.000)	450,363
(9)	Excluding financial crisis	0.4922 ***	(0.000)	360,157
(10)	Time window starting in 2010	0.8831 ***	(0.008)	123,950
(11)	Excluding State New York	0.3634 ***	(0.000)	391,467
(12)	Excluding states deregulated after 1990	0.5295 ***	(0.000)	400,457
(13)	Excluding innovating BHC's state headquarter	0.5408 ***	(0.000)	389,272
(14)	Excluding innovating BHC's county headquarter	0.5436 ***	(0.000)	448,515

Internet Appendix for
"Innovating Banks and Local Lending"

This Internet Appendix contains several additional tables and figures that complement the results presented in the main paper.

Table IA.I: Examiner Leniency

This table provides panel-estimations of banks' deposit growth column (1) to (3) and mortgage growth, respectively, in column (4) to (6) by bank-county-year on banks' innovation from 2002 to 2013. The sample is constructed from all BHC from which we retrieve financial statement data from year-end Call Reports. Patent data are retrieved from the U.S. Patent and Trademark Office (USPTO). Lender controls are retrieved from the Call Reports from the prior year, while borrower controls (not reported) are retrieved from the HMDA database and display average borrower income, loan size-to-income ratio, percent women applicants, and percent minority applicants. We also control for county-characteristics, i.e., percent minorities per county and average income per capita in a county. Regressions (1) to (6) include both US-Region*year fixed effects as well as bank fixed effects (see Acharya et al. (2012)). The U.S. Census Bureau distinguishes four U.S. regions: Northeast, South, Midwest, and West. All accounting data are collected in U.S. Dollar. The variable definitions and data sources are given in Appendix I. P-values are given in parentheses and ***, **, * indicate an estimate that is statistically significantly different from zero at the 1%, 5%, and 10% level, respectively.

	Deposit Growth			Mortgage Growth		
	First Stage	OLS	IV	First Stage	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Patents		0.0199	0.1614*		0.3350***	0.9986***
		(0.249)	(0.065)		(0.000)	(0.000)
Examiner Leniency	1.1450***			1.7148***		
	(0.000)			(0.000)		
C&I loans/Total Assets	-2.4949**	-1.4614	-0.4549	-1.1091**	25.2761***	30.6529***
	(0.015)	(0.109)	(0.690)	(0.017)	(0.000)	(0.000)
Consumer Loans/Total Assets	13.2700***	-1.1435*	-3.2079**	11.9965***	-16.4899***	-22.6507***
	(0.000)	(0.072)	(0.027)	(0.000)	(0.000)	(0.000)
Total Loans/ Total Assets	0.6370**	-0.0909	-0.2008	-2.3660***	6.5114***	6.7100***
	(0.040)	(0.820)	(0.609)	(0.000)	(0.000)	(0.000)
Minorities in county	-0.1189	1.0771**	1.0937**	-0.4101*	0.8917	0.3438
	(0.460)	(0.014)	(0.013)	(0.061)	(0.221)	(0.637)
Income per capita per county	-0.0034**	0.0028	0.0033	-0.0010	-0.0005	0.0002
	(0.021)	(0.388)	(0.304)	(0.247)	(0.882)	(0.962)
Total Assets	0.5457***	0.1869***	0.1501**	0.5215***	-0.1295	-0.3692***
	(0.000)	(0.004)	(0.028)	(0.000)	(0.134)	(0.000)
ROA	-48.8779***	1.3635	7.7347**	-75.3261***	36.8620***	78.4716***
	(0.000)	(0.617)	(0.032)	(0.000)	(0.000)	(0.000)
Noninterest Income/Total Income	3.1285***	-0.0373	-0.4812*	3.4676***	-0.0989	-2.8517***
	(0.000)	(0.754)	(0.084)	(0.000)	(0.623)	(0.000)
Total Deposits/ Total Assets	0.3458	0.4965	0.1971	-1.0223***	-9.6224***	-9.7092***
	(0.272)	(0.232)	(0.690)	(0.000)	(0.000)	(0.000)
Non-performing Loans	13.2915***	0.8850	-1.3205	23.6350***	23.7707***	7.0532***
	(0.000)	(0.326)	(0.479)	(0.000)	(0.000)	(0.000)
				0.0554***	0.3235***	0.2880***
				(0.000)	(0.000)	(0.000)
Borrower controls	No	No	No	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Region*year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,897	14,897	14,897	74,764	74,764	74,764
R^2	0.9675	0.1673		0.9555	0.4459	

Table IA.II: Effect of patent citations on mortgage growth

This table provides panel-estimations of banks' deposit growth column (1) to (3) and mortgage growth, respectively, in column (4) to (6) by bank-county-year on banks' patent citations from 1997 to 2014. Patent data are retrieved from the *U.S. Patent and Trademark Office (USPTO)*. Citations represents the natural logarithm of a bank's total number of citations received on the bank's patents filed. Regressions include both lender and in column (4) to (6) also (unreported) borrower control variables. Lender controls are retrieved from the Call Reports from the prior year, while borrower controls are retrieved from the HMDA database and display average borrower income, loan size-to-income ratio, percent women applicants, and percent minority applicants. We also control for county-characteristics, i.e., percent minorities per county and average income per capita in a county. All regressions also include US-Region*year fixed effects (see Acharya et al. (2012)). The U.S. Census Bureau distinguishes four U.S. regions: Northeast, South, Midwest, and West. All accounting data are collected in U.S. Dollar. The variable definitions and data sources are given in Appendix I. P-values are given in parentheses and ***, **, * indicate an estimate that is statistically significantly different from zero at the 1%, 5%, and 10% level, respectively.

	Deposit Growth			Mortgage Growth		
	First Stage (1)	OLS (2)	IV (3)	First Stage (4)	OLS (5)	IV (6)
Citations		0.0209***	0.0351***		0.1636***	0.4778***
		(0.000)	(0.000)		(0.000)	(0.000)
No of Doctoral degrees	0.3307***			0.2276***		
	(0.000)			(0.000)		
C&I loans/Total Assets	-1.7426***	-0.0654	-0.0260	-0.8194***	-0.2868**	0.1781
	(0.000)	(0.369)	(0.732)	(0.000)	(0.029)	(0.186)
Consumer Loans/Total Assets	6.2587***	-0.1057	-0.2090**	6.3491***	0.9705***	-1.1371***
	(0.000)	(0.167)	(0.023)	(0.000)	(0.000)	(0.000)
Total Loans/ Total Assets	-2.0698***	-0.0443	-0.0115	-3.4286***	0.5139***	1.6095***
	(0.000)	(0.309)	(0.808)	(0.000)	(0.000)	(0.000)
Borrower Income				0.0338***	0.5463***	0.5357***
				(0.000)	(0.000)	(0.000)
Loan size to income				0.0032***	0.0706***	0.0698***
				(0.001)	(0.000)	(0.000)
Women applicants				0.0354***	-0.0774***	-0.0895***
				(0.000)	(0.000)	(0.000)
Minorities applicants				-0.0289***	-0.0615***	-0.0530**
				(0.000)	(0.005)	(0.016)
Minorities in county	-0.4003***	0.0922**	0.0994**	-0.4084***	0.5175***	0.6838***
	(0.000)	(0.039)	(0.027)	(0.000)	(0.000)	(0.000)
Income per capita per county	-0.0019**	-0.0020***	-0.0019***	-0.0011	-0.0025	-0.0019
	(0.013)	(0.004)	(0.005)	(0.128)	(0.109)	(0.214)
Total Assets	0.1508***	-0.0036	-0.0065	0.2730***	-0.0178	-0.1055***
	(0.000)	(0.615)	(0.376)	(0.000)	(0.330)	(0.000)
ROA	1.9160***	0.5574**	0.5551**	3.3474***	4.0084***	3.5900***
	(0.000)	(0.011)	(0.012)	(0.000)	(0.000)	(0.000)
Noninterest Income/Total Income	0.2577***	0.1616***	0.1536***	0.8405***	0.3471***	0.0574
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.398)
Total Deposits/ Total Assets	-1.8470***	0.0810*	0.1125**	-0.5246***	0.9793***	1.1233***
	(0.000)	(0.097)	(0.024)	(0.000)	(0.000)	(0.000)
Nonperforming Loans	7.8742***	-0.1037	-0.2200	5.6211***	0.8693***	-0.8159**
	(0.000)	(0.482)	(0.157)	(0.000)	(0.007)	(0.022)
Region*year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	148,226	148,226	148,226	450,363	450,363	450,363
R^2	0.2077	0.8994		0.3961	0.9338	

Table IA.III: Exclusion of BHCs Headquarters

This table provides panel-estimations of banks' deposit growth column (1) to (4) and mortgage growth, respectively, in column (5) to (8) by bank-county-year on banks' innovation from 1997 to 2014 for branches with exclusion of BHC's state (column (1) and (2)) or county (column (3) and (4)) headquarters. In column (5) to (8) we provide panel-estimations of banks' mortgage growth by bank-county-year on banks' innovation. The sample is constructed from all BHC from which we retrieve financial statement data from year-end Call Reports. Patent data are retrieved from the U.S. Patent and Trademark Office (USPTO). Lender controls are retrieved from the Call Reports from the prior year, while borrower controls (not reported) are retrieved from the HMDA database and display average borrower income, loan size-to-income ratio, percent women applicants, and percent minority applicants. We also control for county-characteristics, i.e., percent minorities per county and average income per capita in a county. Regressions (1) to (6) include both US-Region*year fixed effects as well as bank fixed effects (see Acharya et al. (2012)). The U.S. Census Bureau distinguishes four U.S. regions: Northeast, South, Midwest, and West. All accounting data are collected in U.S. Dollar. The variable definitions and data sources are given in Appendix I. P-values are given in parentheses and ***, **, * indicate an estimate that is statistically significantly different from zero at the 1%, 5%, and 10% level, respectively.

	Deposit Growth				Mortgage Growth			
	First Stage	IV	First Stage	IV	First Stage	IV	First Stage	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	State Exclusion		County Exclusion		State Exclusion		County Exclusion	
Patents		0.0410***		0.0365***		0.5408***		0.5436***
		(0.000)		(0.000)		(0.000)		(0.000)
No of Doctoral degrees	0.3179***		0.3085***		0.2285***		0.2009***	
	(0.000)		(0.000)		(0.000)		(0.000)	
C&I loans/Total Assets	-1.7504***	-0.0056	-2.0418***	-0.0328	-0.6310***	-0.0106	-0.7702***	0.1755
	(0.000)	(0.923)	(0.000)	(0.541)	(0.000)	(0.943)	(0.000)	(0.194)
Consumer Loans/Total Assets	5.7314***	-0.0930	5.5879***	-0.1094	5.3247***	-0.9297***	5.5161***	-1.0970***
	(0.000)	(0.211)	(0.000)	(0.103)	(0.000)	(0.000)	(0.000)	(0.000)
Total Loans/ Total Assets	-1.7517***	0.0330	-1.7988***	0.0219	-2.7518***	1.6757***	-2.7573***	1.4863***
	(0.000)	(0.293)	(0.000)	(0.438)	(0.000)	(0.000)	(0.000)	(0.000)
Minorities in county	0.0586*	-0.0184	0.0808***	-0.0072	-0.3559***	0.7479***	-0.3500***	0.6852***
	(0.077)	(0.505)	(0.009)	(0.771)	(0.000)	(0.000)	(0.000)	(0.000)
Income per capita per county	0.0008	-0.0007	0.0014***	-0.0006	-0.0019***	-0.0022	-0.0020***	-0.0014
	(0.125)	(0.116)	(0.003)	(0.147)	(0.003)	(0.202)	(0.001)	(0.375)
Total Assets	0.1550***	0.0022	0.1473***	0.0003	0.3795***	-0.1857***	0.3402***	-0.1604***
	(0.000)	(0.725)	(0.000)	(0.953)	(0.000)	(0.000)	(0.000)	(0.000)
ROA	1.4461***	0.5077***	1.5191***	0.5167***	3.1037***	3.1675***	3.8029***	3.1769***
	(0.000)	(0.005)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Noninterest Income/Total Income	0.2059***	0.1235***	0.1222***	0.1182***	0.2111***	0.3509***	0.1705***	0.3677***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total Deposits/ Total Assets	-2.1153***	0.0881**	-2.0651***	0.0729**	-0.6976***	1.1693***	-0.7872***	1.2996***
	(0.000)	(0.016)	(0.000)	(0.027)	(0.000)	(0.000)	(0.000)	(0.000)
Nonperforming Loans	7.1294***	-0.5240***	7.7555***	-0.3537***	6.0855***	-1.5808***	6.3635***	-1.6004***
	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Borrower controls					Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region*year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	117,609	117,609	139,660	139,660	389,272	389,272	448,515	448,515
R^2	0.904		0.9035		0.9356		0.9317	