Financial Technology And Local Lending

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ABSTRACT

We study the effects of innovations in financial technology by banks on local competition for deposits and credit supply. To identify the causal effect of financial technology on deposits and lending, we exploit the geographic heterogeneity in human capital available to bank headquarters to explain banks' patenting activities. 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 and small business lending without impairing the quality of their loan portfolio. Finally, we show that the innovation-induced credit supply shock spurs local economic growth and employment.

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.[1] 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 remain relatively unexplored.

In this paper, we show that innovating banks raise more deposits via their branch networks, grant more mortgage loans, and extend small business credit supply. Bank branches that profit from innovations awarded to their parent company are able to attract deposits (and thus customers) in a zero sum game at the expense of local non-innovating competitors. This positive effect on competition is more pronounced in counties in which non-innovative banks branches dominate the market and are challenged by innovative competitors. In contrast, counties in which only branches of innovative banks compete with each other experience an increase in market concentration. 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 and small business 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 and thus less efficient competitors, banks that innovate are able to attract more loan applications, attract better loans, and thus increase their overall loan performance. Finally, we show that the increase

[1] Contemporaneous surveys of the literature on financial technology as well as discussions of market trends are given by Thakor (2019), FSB (2019), and Claessens et al. (2018).

in market power and efficiency induced by innovation leads to a significant increase in local economic growth. Combined, our results provide strong evidence for the importance of technological innovations in banking.

We start our analysis by first documenting a steadily increasing trend in the number of patents awarded to U.S. banks 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 patents for financial innovations (e.g., new derivatives) 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. 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 outcomes at the branch level. Finally, we study the effects of bank innovation on aggregate credit supply and local real growth.

The identification of the causal effect of innovations by banks on lending behavior at their local branch level is challenging for a number of reasons. For example, innovation and firm outcomes 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. Moreover, innovating banks will differ from their non-innovating competitors in firm size and various other ways. To address the latter, we therefore focus in our main analysis on banks that were awarded at least one patent in our sample period of 1996-2015 (see also Cortés et al., 2020, for a similar empirical strategy). To address the former problem, we foremost employ an instrument variable (IV) approach that 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 innovative output by employing the number of PhDs completed in a metropolitan area as a proxy for the human capital available to banks headquartered nearby to verify the causal effect of patents on banks' deposit-taking and lending.[2] Next, the causal relation between bank innovation and outcomes 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 deposit-taking and lending in counties outside a bank'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 county*year 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 exter-

[2] In our robustness checks, we underline our findings with a second IV approach where we follow Gaulé (2018) and instrument for the number of patents awarded to a bank by using differences in leniency across banks' patent examiners as a plausibly exogenous source of variation in the probability of being granted a patent.

nal 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).[3] 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.[4] To the best of our knowledge, however, there is little to no evidence yet on the effect of technological innovations by banks.[5] In the only related papers we are aware of, Pierri and Timmer (2020) find in a contemporaneous study that a higher intensity of IT-adoption led to significantly lower non-performing loans at US banks during the financial crisis. While their paper, however, looks at the effects of IT-adoption on financial stability, the focus of our paper lies on the effects of innovation on deposit flows and credit supply.[6] 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

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

[4] Few, but notable exceptions find empirical (see Henderson and Pearson, 2011; Beck et al., 2016) and theoretical evidence (see Thakor, 2012) 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.

[5] One of the few cross-sectional studies in this field is due to Berger (2002) who looks at the cost-reducing effects of the introduction of information technology (esp. ATMs and computers) by banks in the 1980s and 1990s. More recent studies have looked at the characteristics of fintech patents (see Chen et al., 2019), the effects of introducing financial technology in selected banks (see Berg et al., forthcoming; Fuster et al., 2019), as well as the effects of financial technology adoption on retail businesses and their customers (see Higgins, 2020). However, while these studies concentrate on the role of financial technology in *individual* banks, none of them looks at the aggregate effects of bank innovations on lending in the firm and time domain.

[6] Our evidence on banks' charge-off ratios does support their findings.

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 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 bank 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 crit-

ical 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 affects deposit-taking and lending in remote bank branches. To give our main results even more credibility, in our robustness checks, 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 a bank's innovations with the human capital available near the bank'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 Sample construction

We start the construction of our data sample by combining patent application data from the U.S. Patent and Trademark Office (USPTO) patent assignments record and the USPTO Application Information Retrieval (PAIR) database with bank commercial lending data from U.S. Call Reports.

In our main analysis, we concentrate on those banks that have been granted at least one patent in our sample period between 1997 and 2016 and that make housing-related loans in any U.S. state.[7]

Next, we match our data to the Summary of Deposits database from the Federal Deposit Insurance Corporation (FDIC) to enrich our sample with information on each innovating bank's number of branches and the amount of deposits held via each of its branches in the U.S. during our sample period. Complementing the data on bank deposits, we combine our data on banks' balance sheets and income statements as well as patenting activity with mortgage origination data from the Home Mortgage Disclosure Act (HMDA). Finally, to analyze the potential effects of bank innovation on small business lending, we supplement our sample with Community Reinvestment Act (CRA) loan origination data collected by the Federal Financial Institutions Examination Council (FFIEC).

Our final sample then consists of 26,324 bank-county-year observations (deposit data), 89,441 bank-branch-year observations (mortgage loan data), and 126,264 bank-branch-year observations (small business loan data) coming from 77 unique innovating banks during our sample period, making our sample comparable in size to the ones used in related studies (see, e.g., Gilje et al., 2016; Cortés et al., 2020). [8]

2.2 Bank innovation

For each bank, we collect bank-year patent and citation information from the USPTO patent assignments record and from the 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.[9]

To get a better understanding of the nature of innovations by banks, we first divide the universe

[7]In additional analyses in the Internet Appendix, we show that our main findings also hold in a sample that includes both innovating and non-innovating commercial banks. However, as mentioned in the introduction, innovating and non-innovating banks will differ along various dimensions making identification in these analyses less compelling.

[8]Sample sizes differ as the HMDA data on the sample banks' mortgage loans are available at the bank-county-level, while the FDIC's data on the deposits held by a bank are available at the bank-branch-level.

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

of banks' patents into two broad subcategories: financial and technological 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 *Technological Patents*.[10]

The broad categorization of banks' patents into financial and technological (i.e., process) innovations is helpful to get a first impression of the innovative activities of banks, but dates back to a pre-fintech time in which technological 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) as these are clearly identifiable via their respective patent subclasses. The remaining patents belong to various subclasses thus necessitating a manual categorization. We start by building a category for patents that are related to online and/or mobile banking at the front-end of a bank's business. Similarly, a large portion of the bank patents in our sample are related to banks' automated teller machines (ATMs) and payment services. Finally, as our sixth patent category, we manually screen bank patents and identify those that are related to improvements in a bank's back office operations and IT infrastructure.[11] Outliers, such as innovations on insurance products or in non-finance related areas (e.g., chemical industry) are deleted from our final sample. In summary, our sample includes a total number of 3,773 patents in six categories that were applied and later granted to banks domiciled in the U.S.[12]

[10]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.

[11]For each patent category, an exemplary patent application is shown in Section IA.1 in the Internet Appendix.

[12]Note that our sample is almost three times larger than the fintech patent sample identified for banks by Chen et al. (2019). However, while we include non-fintech patents as well, their full sample includes a considerable number of

We then proxy for a bank's innovation productivity by using two variables based on a bank's patents. The first measure is a bank's number of patents filed (and later granted) 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 2016. This allows us to verify that all patent applications are also granted in the subsequent years.[13]

While the number of 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 measures 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.[14]

2.3 Bank data

We compile balance sheet and income data from U.S. call reports, as is standard in the literature. Accounting variables at the bank-level are later used in our regressions of the deposit,

patents awarded to non-bank entities.

[13]In contrast to previous studies that show a two-year lag between patent application and patent grant, on average, bank patents in our sample are characterized by an average lag of about 4 years between the time a patent is applied and finally granted.

[14]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.

mortgage, and small business loan 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. These data are then merged with the FDIC's Summary of Deposits and HMDA databases. 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 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 and year 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 are interested in capturing the effect of bank innovation on banks' small business lending activity. More precisely, we exploit Community Reinvestment Act (CRA) loan originations data from 1996 to 2016 collected by the FFIEC at the subsidiary bank level. CRA data provide loan data with commitment amounts below \$ 1 million originated from financial institutions with total assets exceeding \$ 1 billion. From the CRA data, we then employ information on banks' small business lending activities within a given county and year. We follow Cortés et al. (2020) and use the CRA data to build an annual growth rate of new loan originations below \$ 1 million and measure our loan growth measures as follows:

$$Loan\ growth_{i,j,t} = \frac{Loan\ originations_{i,j,t} - Loan\ originations_{i,j,t-1}}{(Loan\ originations_{i,j,t} + Loan\ originations_{i,j,t-1})/2} \tag{1}$$

where i represents the bank, j represents county, and t represents year. Note that defining the loan growth rate in this way yields a variable that is defined on the interval $[-2; 2]$ to mitigate the effect of outliers.

2.4 Descriptive statistics

Figure 1 exhibits the time evolution of the patents granted to U.S. banks between 1997 and 2016. In total, our sample includes a total number of 3,773 patents that were applied and later granted to banks domiciled in the U.S.

[Place Figure 1 about here]

Panel A of Figure 1 shows that the average number of granted patents of banks increased steadily to more than 300 patents in 2010. 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 granted patents increasing again by 2010.

Panel B of Figure 1 plots the time evolution of patents by categories (financial vs. technological). The plot shows that the number of financial and technological patents remained at a constant low level until the year 2000. After 2000, the numbers of financial and technological patent grants evolve quite differently. On the one hand, the number of financial patents experienced a small increase until 2010 and then sharply declined in subsequent years. Technological patents, on the other hand, became more relevant. The average number of granted technological patent increased to 231 shortly before the financial crisis and slightly decreased thereafter. After this small dip, the number of technological patents increased again to its maximum of 364 technological patents in the final year of our sample. In total, banks applied for (and were granted) 618 financial and 3,155 technological patents.

To get a better understanding of the fields in which banks innovate, Figure 2 plots the time evolution of the number of granted bank patents in each of our six patent categories.

[Place Figure 2 about here]

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 2006 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. This focus of the majority of banks' patents on technology and IT is also reflected in the word cloud shown in Figure 3 made on the basis of all patent applications' abstracts.

[Place Figure 3 about here]

This first descriptive evidence on the nature of our sample patents thus clearly highlights the technological revolution that took place in the banking sector well before the advent of blockchain and cryptocurrencies.

Next, we report summary statistics for our sample of innovating banks (i.e., banks that were granted at least one patent during our whole sample period) in Table I.

[Place Table I about here]

Panel A of Table I provides information on our sample banks' granted patents. On average, the sample of innovating banks were granted 12 patents per year. Of these patents, 2 were of financial and 10 of technological nature. Going into more detail, we can see from six patent categories that the fewest patents were granted for financial product innovations (0.702) while banks innovated heavily in the fields of general operations and IT (5.136) and online/mobile banking (2.513

granted patents per year on average). Again, the summary statistics underline our first impression that financial innovations have become less and less important for banks while innovations in IT, online/mobile banking, and even ATMs have dominated banks' R&D activities during our sample period.

In Panel B of Table I, we show summary statistics of the data on our sample banks' mortgage lending activity. Data in this Panel are annually collected from the HMDA database 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, information on loan approval or the rejection reason, the identity of the lender, the location of the property, and the geographical location of the borrower. Similar to Gilje et al. (2016), we employ information on borrowers' income, the loan size to income ratio, and both the percentage of women and minority applicants as control variables in our empirical analyses. From the averages given in Panel B, we can see that the average mortgage growth level of innovating banks in our sample is 26.9%. Also, innovating banks see their mean total deposits and small business loans grow annually by 4.6% and 6.7%, respectively.

Summary statistics for our sample banks' financial statement variables are given in Panel C of Table I. The table shows that, as expected, innovating banks are comparably large, are well capitalized, are profitable on average, and have a mean deposit to total assets ratio of about 71%. Moreover, they engage in non-lending activities as evidenced by their noninterest income ratio and have a substantial portion of mortgage loans in their portfolio (11.5% of their total assets on average).

Finally, Panel D of Table I shows the average number of doctoral degrees. Data is provided on MSA-year level and is retrieved from the National Science Foundation and the HERD survey.

3 Identification Strategy

We analyze how variation in the level of innovation at banks 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 bank and the branch level, we try to identify the causal link between bank innovation and branch-level outcomes by using an instrumental variable approach.

In our empirical analysis, we employ the availability of human capital in the vicinity of a bank's headquarters as an instrument for bank innovation.[15] In particular, we estimate the two-stage regression model

$$\begin{aligned} Innovation_{i,l,t} &= \alpha_1 Human\ Capital_{l,t-1} + \alpha_2 \mathbf{x}_{1,i,l,t-1} + \alpha_3 \mathbf{x}_{2,j,t-1} \quad (2) \\ &+ \gamma_i + \eta_t * \lambda_j + \varepsilon_{i,b,j,l,t} \\ Outcomes_{i,b,j,l,t} &= \beta_1 \widehat{Innovation}_{i,l,t-1} + \beta_2 \mathbf{x}_{1,i,l,t-1} + \beta_3 \mathbf{x}_{2,j,t-1} \quad (3) \\ &+ \gamma_i + \eta_t * \lambda_j + \epsilon_{i,b,j,l,t} \end{aligned}$$

where i indexes a bank headquartered in Metropolitan Statistical Area (MSA) l operating branch b in county j 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 bank's patents. $Human\ Capital_{l,t}$ is our instrument variable defined as the average number of doctoral degrees awarded in year t in MSA l with the data being retrieved from HERD. Our main focus lies on the estimates for the parameter β_1, the effect of bank innovation at the bank level on our outcome variables $Outcomes_{i,b,j,l,t}$ 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 bank'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 bank's headquarter with employees who in turn

[15] In Section IA.2 in the Internet Appendix, we 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. All main findings are robust to this alternative identification strategy.

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 bank causing reverse causality. Additionally, overall business success of a bank 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 bank (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 bank 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 bank-fixed effects to control for unobserved factors co-determining bank innovation and estimate all our regressions using standard errors clustered at the bank level.

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 bank'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 bank's home state (county). As a result, local factors that drive outcomes at the bank 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 bank'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 bank'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 county*year fixed effects to control for time-varying local demand effects. Moreover, our robustness checks in which we only include bank branch observations that are geographically distant from the respective bank's headquarter should also mitigate the concern of an omitted variable bias stemming from local demand effects.

4 Results

4.1 Baseline Results - Local Deposits

We start our investigation into the effects of innovation on bank performance at the local level by estimating regressions of the growth in deposits by bank-county-year on the (log) number of patents. We estimate both ordinary least squares (OLS) and IV regressions, saturate our regressions with lagged bank controls as well as bank-fixed and county*year fixed effects, and employ standard errors clustered at the bank level. Our main explanatory variable in all these regressions is 1 + the lagged number of patents granted to a bank. Table II presents the results from OLS regressions as well as the first and second stage results from IV regressions using $Human\ Capital$ as our instrument.

[Place Table II about here]

The IV results in column (3) of Table II show a statistically significantly positive effect of innovation on local deposit growth. A one percent increase in the (log) number of patents leads

to a 14 BP (see column (3), $0.1452 * ln(101/100)$) increase in deposits per year. We thus find a strong indication that more innovative banks are able to attract more customer deposits. 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 column (2) is statistically insignificant. Taken together with the estimates in our IV specification, the results are thus indicative of a "corrective endogeneity" (cf. Jiang, 2017) with the sample correlation between bank innovation and deposit growth understating the true effect.[16] Next, we try to analyze in more detail the question which *types* of bank innovation drive the positive relation between innovation and the growth in deposits. As instrumenting for six endogenous variables at the same time is not feasible in our setting, we resort to an OLS estimation in column (4) in which we include all six patent categories at the same time. Keeping in mind that our identification strategy is not available in this setting, the results are nevertheless in line with our expectations.[17] The patent categories that capture innovations which are unrelated to deposit accounts (Financial Product Innovations, Credit Risk Processing, and Portfolio Selection & Trading) are significantly negatively related to deposit growth. In contrast, and in line with our intuition, patents that involve improvements of ATMs have a strong significant and positive effect on deposit growth at banks. Similarly, general innovations in bank IT operations and processes also have a positive and statistically significant impact on the growth of bank deposits.

4.2 Baseline Results - Local Mortgage Lending

The results so far show that local bank branches are able to take in significantly more deposits the more innovative the branches' parent bank is. To answer the question whether these liquidity shocks help banks overcome financing frictions and extend their lending, we now analyze the

[16]Assuming that our model can plausibly account for any omitted variable bias, the finding of a negative bias in the OLS estimate is likely caused by reverse causality that drives patents up for banks with low growth rates in deposits and vice versa. This is in line with our intuition and current industry trends as absent any competitive pressure, banks have historically been quite sluggish in investing in innovation.

[17]As described earlier, even though we do not instrument for our six patent category variables in column (4) of Table II, we expect that the OLS coefficients will likely underestimate the true effect of innovation types on deposit growth.

changes in mortgage loan originations. More precisely, we again estimate the IV specification in Equations (2) and (3) where we employ the percentage growth in mortgage loans at the branch-year level as our outcome variable.

[Place Table III about here]

Table III presents the estimation results from the IV panel-regressions together with the results of OLS regressions for our $Patents$ variable as well as the variables built from the individual patent categories. We find bank innovation to have a significant and positive effect on total mortgage growth in both our OLS regression in column (1) as well as in the second stage of our IV specification in column (3). The found statistically significant results are also economically significant. In our baseline IV regression, a one percent increase in our innovation proxy is associated with a 0.39% (see column (3), $0.4007 * ln(101/100)$) increase in mortgage lending per branch. As with our regressions of banks' growth in deposits, our proxy for $Human\ Capital$ is a strong predictor of banks' patenting activities with the IV regression passing the Kleibergen-Paak tests easily. Moreover, we find the positive effect of bank innovation on mortgage lending to be statistically significant in both the OLS and IV regressions, with the OLS estimate again appearing to underestimate the true causal effect. In column (4), we estimate an OLS regression in which we decompose our bank patent variable into the six predefined patent categories. The results reveal a differential effect of the patent categories on mortgage growth. Financial Product Innovations enter regression (4) with a statistically significant negative coefficient, a result which is in line with our expectations given that most financial innovations are related to investment banking rather than a bank's lending activities. In contrast, we can again see that innovations in areas with direct bank-customer interaction (ATMs and online/mobile banking) as well as innovations that improve backoffice operations have a statistically significant and positive effect on mortgage loan growth. Finally, innovations in Credit Risk Processing enter column (4) with an insignificant coefficient though this result is most likely due to the low number of patents in this category.

4.3 Baseline Results - Local Small Business Lending

Next, we evaluate the effect of bank innovation on small business lending. Our previous results hint at a positive effect of bank innovation with local branches experiencing liquidity windfalls in case of innovation spillovers from their headquarter. While branches appear to use this additional liquidity and extend credit supply in the mortgage market, the overall effect of bank innovation on lending remains unclear. Ideally, branches of innovative banks would use the additional deposit inflows as well as the technological advantage over competitors to increase lending in all market segments. However, we cannot rule out that innovative banks simply become more selective and shift their engagement in firm loans to the mortgage sector. To get a better idea of the innovation-induced effects on bank lending, we next try to explain the growth rate in new loan originations below $ 1 million.

[Place Table IV about here]

Table IV reports regressions of the growth in small business loans as a function of our bank innovation proxy. We include the same set of lagged bank characteristics as before and include bank and county*time fixed effects. We again report both the estimates from the OLS and IV regressions, as well as an OLS regression in which we decompose our Patents variable into the six patent categories. The results provide no support for banks substituting firm loans for mortgage loans. In fact, the effect of bank innovation on loan growth is even stronger for the CRA loan originations than for the HMDA mortgage loans. In addition to being highly statistically significant, the positive effect of a bank's patents on CRA loan growth is also highly economically significant. A one percent increase in the number of granted patents is associated with a 1.47% (see column (3), $1.4736 * ln(101/100)$) increase in small business loan originations. Again, the OLS estimate significantly underestimates the effect we find in our IV specification. Finally, the OLS regression reported in column (4) in which we split our innovation proxy according to our six patent categories hints at the underlying channels driving the positive effect of innovation on firm lending. Improvements in ATMs and online/mobile banking (i.e., processes related to direct customer-bank

interactions and the bank's point-of-sale) which were previously found to be driving the increase in mortgage loan originations, now enter the regression in column (4) with a significant negative coefficient. At the same time, innovations that we would expect to matter more for business rather than retail customers (financial product innovations and credit risk processing) now positively affect firm lending. Finally, improvements in backoffice processes and general IT that could improve both corporate and retail banking also have a positive effect on small business lending.

4.4 Results for local and nonlocal markets

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 (i.e., without any improvement in their lending technology), 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 bank 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 nonlocal markets. The results of these regressions are reported in Table V. We report only the coefficient on our main variable *Patents*, but all specifications include the same set of controls and county*year as well as bank fixed effects as our previous sets of regressions.

[Place Table V about here]

Bank innovations have a positive and significant impact on loan mortgage growth regardless of whether a bank operates a branch in a given county, or not. The statistical and economic significance of the effects in both subsamples are approx. of the same magnitude as before in our baseline regression though the effect is stronger in local markets. For the CRA loans, results for local and nonlocal markets differ from those previously found for our full sample. First, we find *no* empirical support for a positive effect of bank innovation on small firm lending in local markets. In contrast, innovations lead to a highly significant increase in small business lending in areas where the bank operates no branches. In other words, innovating banks do not extend credit supply to firms indiscriminately, but selectively originate more small business loans in nonlocal markets. For mortgage lending, it thus seems as if innovative banks exploit both the innovation-induced liquidity shock as well as technological advances that reduce information asymmetries between banks and borrowers to extend credit supply in both local and nonlocal markets. For business loans that should be subject to more pronounced contracting frictions, however, our subsample analysis points at a different channel driving our results. As innovative banks venture into nonlocal markets only, the increase in firm lending is most likely due to a reduction in information asymmetries due to technological innovations (rather than the mere increase in liquidity). A result that is supported by our previous findings in column (4) of Table IV where we showed that advances in credit risk management and loan processing significantly increased firm lending.

4.5 Innovative Banks Attract Cheaper Deposits And More Loan Applications

Up to this point, our findings indicate that local bank branches extend their credit supply as a result of innovation shocks spilling over from the respective bank headquarters. Taken together with our findings on branches' innovation-induced increase in deposits, these results support the hypothesis that innovations help banks lift financing constraints and attract new customers when it comes to mortgage and small business 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. In this respect, 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. 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 VI about here]

Table VI presents the results of branch-year-level regressions in which we first employ the natural logarithm of the number of loan applications (column (1)) and the fraction of granted loans as a percentage of the total number of loan applications (column (2)) as dependent variables. Complementing these analyses, we estimate regressions at the bank-year-level in which we use the change in interest expenses over deposits (column (3)) and the fraction of mortgage loans that were charged off or are delinquent (90 days or more past due or nonaccruing; column (4)) as our outcome variable of interest. For all regressions, we report IV estimates for the (log) number of patents using our proxy for human capital as an instrument. Furthermore, we include our previous sets of covariates and include bank, year (bank level), and county*year (branch level) fixed effects.

The results in columns (1) and (2) show clearly that innovations increase the number of loan applications and increase average acceptance rates. In line with the hypothesis of innovations enabling banks to attract depositors (and thus new customers) to which banks can subsequently cross-sell loans, innovative banks receive significantly more applications for mortgage loans. At the same time, more innovative banks seem to be more lenient in their selection of investment projects with acceptance rates for loan applications increasing significantly. We can think of (at least) two competing explanations for this finding. On the one hand, if innovations help banks to lift financing constraints, these local deposit inflows to branches could enable banks to cater loans to previously underserved customers thus increasing overall loan acceptance rates. On the other hand, the increase in acceptance rates could be due to agency problems that overshadow the

otherwise positive effects of bank innovation. The results of our regressions of banks' deposit costs and loan quality at the bank-level in columns (3) and (4) support the first line of reasoning. We find that bank innovations have a weakly significantly decreasing effect on banks' overall costs of deposits. Moreover, we find no evidence that would hint at a deterioration in the quality of banks' loan portfolios (and thus the agency hypothesis).[18] In summary, we find that innovative banks have lower costs of deposit financing, receive more loan applications (as a result of their stronger position in local markets), but also increase loan acceptance rates with overall loan portfolio quality being untarnished by this extension of credit supply.

4.6 Does Local Age Structure Affect The Innovation-Lending Nexus?

The vast majority of banks' patents in our sample come from the realm of information technology. In fact, as evidenced by Figure 2, banks have innovated especially with respect to online and mobile banking as well as process improvements in computer systems (including ATMs) since the start of the Information Age. If bank customers indeed respond to some banks offering more innovative banking services than others, the positive effect of bank innovation on deposit inflows and lending should be more pronounced in counties with a younger average population (see, e.g., Hargittai and Hinnant, 2008, for the intuitive notion that internet use is higher for young people). To test this idea, Table VII splits our sample into two subsamples that only contain those counties with a predominantly young (old) population. To be precise, we build our first subsample of counties with a disproportionately young population by only keeping those observations from our full sample that come from U.S. counties in which the population in the age group of 19-39 years makes up at least 25% of the respective counties' overall population. In a similar fashion, we define the subsample of counties with a predominantly old population by requiring the observations to come from counties in which more than 25% of the population are 65 years old or older. Again, we only report the coefficients of interest with the regression specification being the same as in our

[18]We additionally report Anderson-Rubin weak identification test results in these regressions to rule out that our regressions at the bank-level suffers from weak identification.

previous regressions at the bank-branch-county level.

[Place Table VII about here]

As can be seen from the IV results in columns (1) to (3) in Table VII, bank innovation continues to be a significant driver of deposit intakes and mortgage as well as small business lending. The results we find for the subsample of counties with a younger population are thus consistent with the idea that young people respond more strongly to (esp. IT-related) innovations by banks. Moreover, the coefficient on our main explanatory variable *Patents* in these regressions is both highly statistically significant and, in the regressions of the growth in deposits and mortgage loans, also of the same order of magnitude than in our baseline regressions. As one would expect, the effect of bank innovations on small business loans is somewhat weaker in these counties than in our baseline analysis though the coefficient remains highly statistically significant. For counties in which a large part of the population is over the age of 65, the effect of bank innovations on changes in deposits and mortgage lending is no longer significant, and the effect on small business lending is weakly significant at the 10% level. The results in Table VII thus underpin the notion that innovations help banks attract retail customers only in markets in which (potential) customers should be more open to technological advances.

4.7 Local Aggregate Effects

Our results so far show a causal effect of innovation at banks on local liquidity inflows, mortgage lending, and small business 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 and business loans. While the exogenous propagation of the innovation shock from a distant bank heandquarter 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 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 regressions is the *Share of Innovating Banks* which we estimate by taking the number of branches of bank that were granted at least one patent in a year in a given county as a percentage of all bank branches in that respective county and year (see also Degryse and Ongena, 2005, 2007; Bircan and De Haas, 2019, for a similar proxy of bank concentration). In Figure 4, we first plot the geographical variation in the *Share of Innovating Banks* across U.S. counties in the years 1998,and 2013, respectively.[19]

[Place Figure 4 about here]

Figure 4 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 bank 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 banks presumably cutting down R&D costs, and increased again to the end of our sample period.

[19] Note that while we exclude counties in which banks are headquartered from some regressions in our robustness checks, we nevertheless plot these counties in Figure 4 to show a clear(er) picture of the geographical variation in the local market penetration of innovative banks.

Next, we estimate the growth in total deposits, the number of bank branches, as well as mortgage loans and small business loans (SBL) 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* and 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; Cortés et al., 2020).

[Place Table VIII about here]

Table VIII presents the results of the regressions at the aggregate county-year level. The evidence presented in column (1) shows clearly that the share of innovating bank branches does not affect the total aggregate deposits in a given county. At the same time, a higher market penetration of innovating banks has an increasing effect on the total number of local bank branches in a county as evidenced by the results in column (2). Taken together with our previous result that innovations help banks to take in more deposits, 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 innovating 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 innovating bank branches to test whether an increase in the overall innovation of a county's local banks leads to higher competition in local banking markets. With more and more bank branches having access to innovations, we would then expect this first-mover advantage of innovating banks to vanish with local bank markets becoming more concentrated as less innovative banks are driven out. The baseline test based on our full sample reported in column (5) in Panel B of Table VIII supports the latter hypothesis. A higher share of innovating bank branches is associated with a significantly higher local bank branch concentration. To test the conjecture that bank innovations initially lead to an increase in local bank market competition, we build two subsamples that contain only those observations in counties with a low share of

innovating banks (column (6); share of innovating banks less than 5%), and counties with a high share of innovating banks (column (7); 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 market competition, but only in the subsample of counties in which innovating banks still only have a small market share. In the subsample of counties where the majority of banks is innovating, this effect is reversed with a higher share of innovating banks leading to an even more concentrated local bank market. As one would expect, innovations by banks (just like for industrial firms) lead to a "gale of creative destruction" that manifests itself first in an increase in competition with innovators gaining market power and ultimately in a more concentrated bank market.[20]

Next, we evaluate the effect of bank innovation in a county on aggregate mortgage and small business loans. As bank innovations seem to lead to a redistribution, and not an expansion of deposits, one could argue that home mortgage and firm 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 columns (3) and (4) of Table VIII, we test this relation. The coefficients on the share of innovating banks in a county is statistically significant and positive in both regressions of mortgage loan and small business loan growth. The higher the share of innovative banks in a given county, the higher the growth in total mortgage and small business loans in that county. The results in Table VIII thus establish that bank innovations foster competition for local deposits leading to a higher bank concentration and stimulating overall lending.

The results presented in Panels A and B of Table VIII suggest that a higher market penetration by innovating banks spurs local competition for deposits and has a beneficial effect on both mort-

[20]It could be argued that companies commercialize innovations through cooperation rather than through a fight for market shares. In line with this notion, several studies have stressed that some industry sectors (e.g., biotechnology) are characterized by cooperation between start-up innovators and more established firms, rather than creative destruction (see, e.g., Lerner and Merges, 1998; Gans and Stern, 2003). As Gans et al. (2002) show, however, especially innovations in IT are often commercialized through product market competition and not through cooperation. With the vast majority of bank patents in our sample coming from the realm of information technology, our finding that bank innovation increases local bank market competition is in line with what we would expect.

gage and small business lending. An important question in this context is, whether these effects translate into significant *real effects*. To test this, we perform additional regressions in Panel C of Table VIII in which we explain growth rates in local GDP, household income, and employment. The results show a clear picture with the share of innovating banks in a county being significantly positively related to all our outcome variables. Thus, innovations by banks do not only lead to higher competitive pressure among banks but also supports economic growth via banks' lending channel.

4.8 Robustness Checks

To give our main results more credibility, we expose our main analyses to a battery of robustness checks. Table IX reports the results of this wide set of robustness tests on the found impact of banks' innovation activities on deposit growth (Panel A), mortgage lending (Panel B), and small business lending (Panel C).

[Place Table IX about here]

The results are reported in rows and represent IV-estimations using the number of Doctoral Degrees (except in row (1)) as our instrument for bank innovation. To save space, we only report the coefficient on our main variable of interest in each regression.

First, we implement our alternative identification strategy as laid out in Section IA.2 in the Internet Appendix 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 banks' deposit, mortgage, and small business loan growth.

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In row (2) of Table IX, 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.

We also evaluate whether the direction of the effect of bank innovation on deposit, mortgage, and small business loan growth changes when excluding the financial crisis of 2007-2009 from our sample. They do not, as the results in row (3) still indicate a positive effect of bank innovation on both local deposit growth and lending.

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).[21] For this reason, we use the variable *Citations* (row (4)), which represents the average number of citations per patent that a bank applies for in a given year (see also Tian and Wang, 2011). The results are presented in detail in the Internet Appendix in Table IA.II. Additionally, to capture the importance of each patent, we follow Tian and Wang (2011) and construct in row (5) 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 (6) by counting the total number of citations each patent receives in the first five years after its respective application. 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.

In our additional analyses in Section 4.6, we found that our main results remained significant in those counties in which more than 25% of the population were in the age group of 19-39 years while the opposite was true for counties with a predominantly elderly population. To test the robustness of our findings, we consider in the robustness check in row (7) the effect of bank innovation in those counties that remain in our sample after excluding counties with a high share

[21] 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.

of young and old populations. In other words, we check whether our main findings are robust to an exclusion of county outliers with respect to the average age of the population. Our findings reveal that bank innovation still has a significant effect on deposit, mortgage, and small business loan growth.

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).[22] 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 banks 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 row (8) of Table IX, 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.[23] To further rule out such an endogeneity issue, we exclude the innovating banks' headquarter states (row (9)) and counties (row (10)) in two additional robustness checks. By doing so, we minimize the probability that branches located in the banks' headquarter state or county could benefit disproportionately from the proximity to the headquarter, 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 both Table IA.III and Table

[22]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).

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

IA.IV in the Internet Appendix. Again, our main findings remain statistically and economically similar to those of our baseline estimations. In addition to our panel estimations with county*year fixed effects to control for time-varying local demand effects, we repeat our regressions estimating on top banks' headquarter county fixed effects (row (11)) to control for regional effects on the banks' headquarter county-level that could affect banks' local deposit-taking or lending activity. However, our main findings remain statistically and economically similar to those of our baseline panel estimations. In row (12), we repeat the robustness-check in row (1) using again our instrument *Leniency* and additionally control for banks' headquarter county fixed effects. Our findings remain statistically and economically similar to those in row (1).

Silicon Valley is well known as an international center for high technology and innovation. We therefore exclude the state of California (row (13)) to rule out any biasing effect in this region that could affect both banks' deposit-taking and lending activity. However, the results show that this exclusion does not affect our findings significantly. 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 banks and the highest number of average bank patent applications in our sample. Row (14) in Panels A, B, and C of Table IX shows that the exclusion of these observations does not affect our main results.

5 Conclusion

In this paper, we study the effect of bank innovation on deposit taking and 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, mortgage lending, as well as small business lending. Innovation shocks spilling over from banks 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 financial technology. Innovative banks then make use of this additional (cheaper) liquidity, as well as the innovations in processes, operations, and online/mobile banking itselves, to expand credit supply to home owners and firms. However, rather than just taking lending business away from non-innovators, financial technology also increases aggregate lending, with overall credit supply 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 while at the same time keeping the overall quality of their loan portfolio constant. Finally, we show that the innovation-induced expansion of credit supply spurs local economic growth and employment.

Our paper provides first cross-sectional evidence of an 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. 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 improve banks' financing and efficiency, thereby increasing aggregate mortgage and small business 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 financial technology enables banks to expand their lending not only to mortgage lenders but also firms.

Appendix I: Variable definitions and data sources.

The appendix presents definitions for all dependent and independent variables that are used in the empirical study. Data on bank branches are retrieved from the FDIC Summary of Deposits database while patent data are retrieved from the *U.S. Patent and Trademark Office (USPTO)*. Variables on mortgage home and small business lending are retrieved from both annual HMDA data and the CRA database. Banks' financial statement data are taken from year-end Call Reports.

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).
Technological Patents	Total number of applied technological (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 I: Variable definitions and data sources. (continued)

Variable	Description	
Bank variables		
Total Assets	Natural logarithm of a bank's total assets at fiscal year end.	Call Reports.
Total Deposit/Total Assets	Total deposits divided by total assets.	Call Reports.
Equity Ratio	Total equity divided by total assets.	Call Reports.
ROA	Return on Assets defined as net income over total assets.	Call Reports.
Total Loans/ Total Assets	Total deposits divided by total assets.	Call Reports.
Noninterest Income/Total Income	Noninterest income divided by total income.	Call Reports.
Mortgages/Total Assets	Total mortgages divided by total assets.	HMDA.
Deposit and Loan application variables		
Deposit Growth	Banks' annual deposit growth rate (see Cortés et al. (2020)).	SOD.
Mortgage Growth	Banks' annual mortgage growth rate (see Cortés et al. (2020)).	HMDA.
Small Business Loan Growth	Banks' annual growth rate of new loan originations under $1 million level per year (see Cortés et al. (2020)).	CRA.
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		
No of Doctoral degrees	Average number of awarded doctoral degrees (all sciences) per MSA and per year .	NSF (HERD).
Share of innovating banks	Share of innovating bank branches divided by all branches per county and per year .	HMDA and SOD; own calculation.
GDP growth	GDP growth per county and per year .	NBER Census data.
Minorities in county	Percentage of minorities per county and per year .	NBER Census data.
Income growth	Average income growth in a county per year .	NBER Census data.
Population growth	Average income per capita in a county per year .	NBER Census data.
HHI	Herfindahl Hirshman Index per county and year .	Own calculation based on SOD data.

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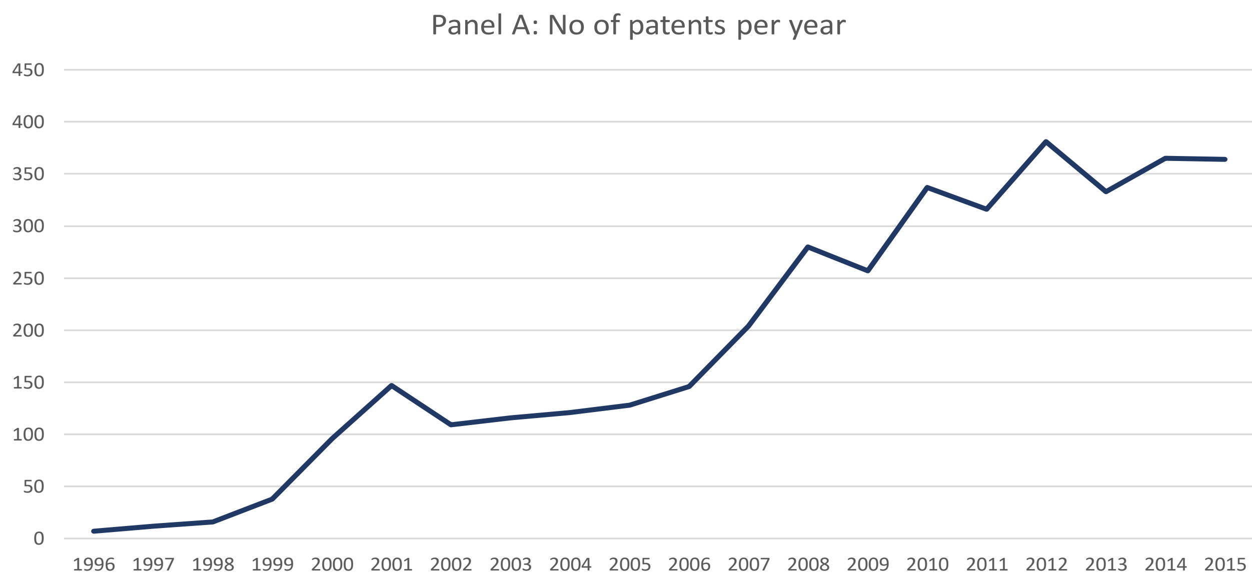
Figure 1: No of patents per year, 1996-2015.

This figure presents the time evolution of the total number of U.S. banks' applied (and later granted) patents between 1996 and 2015. While Panel A shows the total number of all applied and subsequently granted patents, Panel B plots patents categorized as financial and technological patents per year following the categorization by Lerner (2002). Patent data are retrieved from the *U.S. Patent and Trademark Office (USPTO)*.



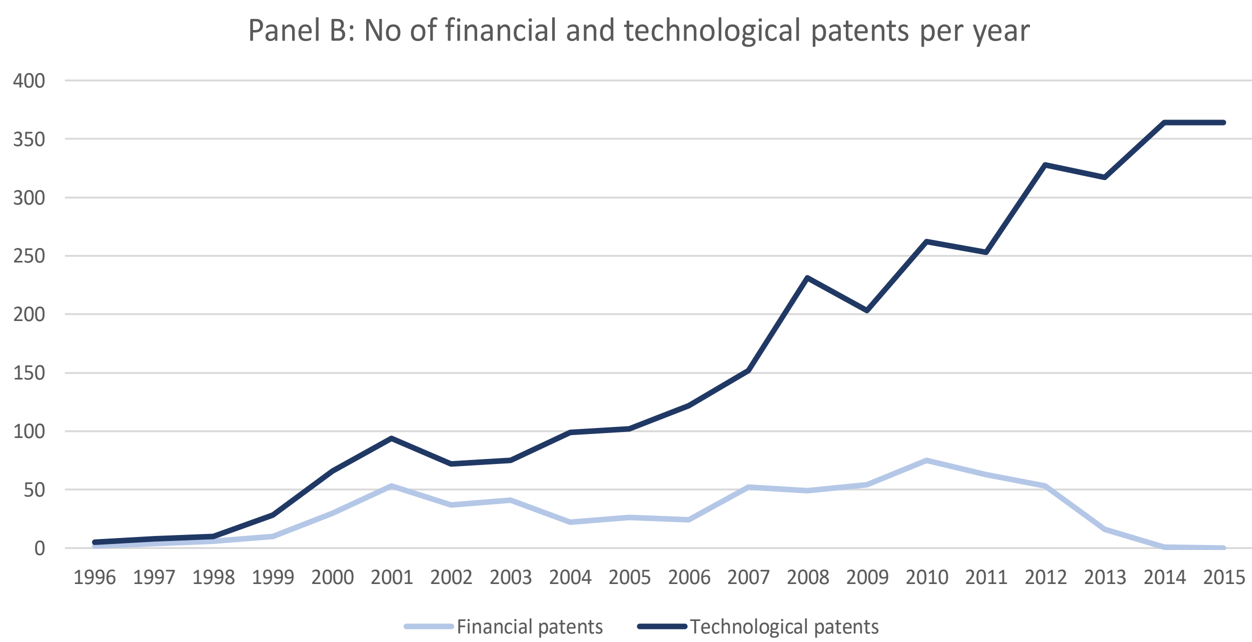


Figure 2: No of patents per category and year, 1996-2015.

This figure presents the time evolution of the total number of U.S. banks' applied (and later granted) patents between 1996 and 2015 classified into six patent categories. Patent data are retrieved from the *U.S. Patent and Trademark Office (USPTO)*.

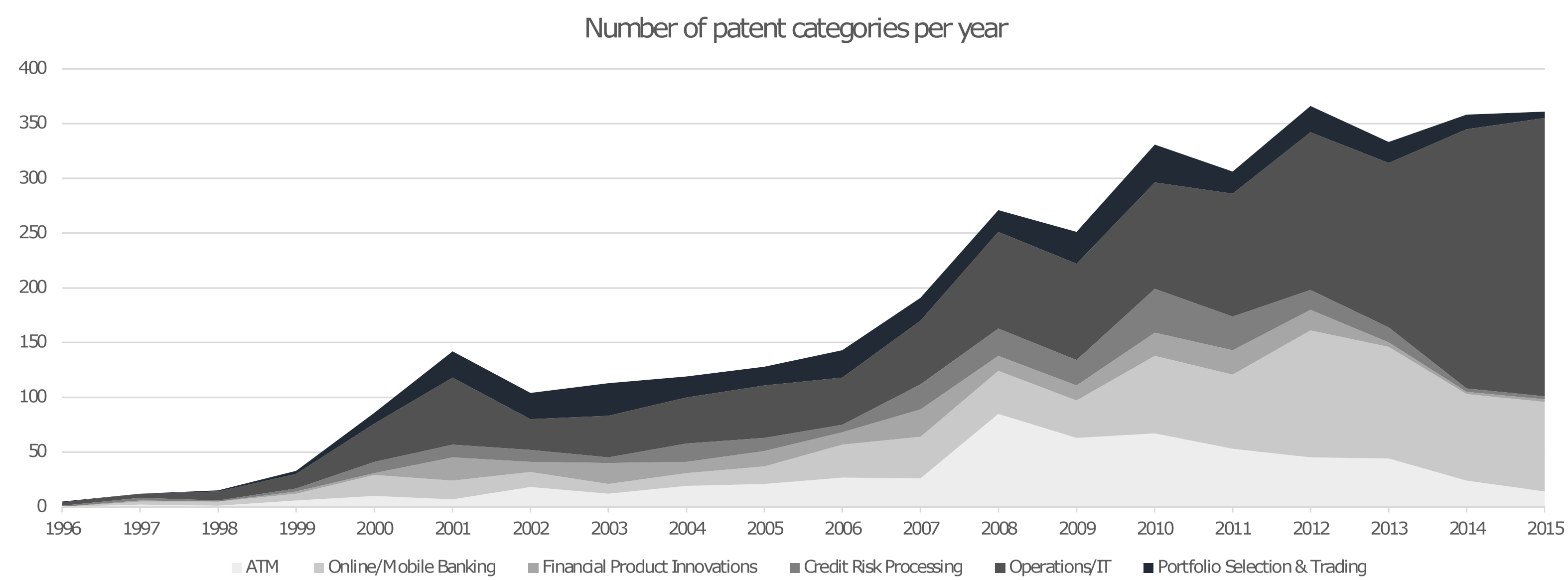


Figure 3: Word cloud of the most frequently used words in U.S. banks' successful patent applications, 1996-2015.

The figure shows a word cloud made from the abstracts of the patent applications applied by and granted to the U.S. banks in our sample between 1996 and 2015. Patent data are retrieved from the *U.S. Patent and Trademark Office (USPTO)*.

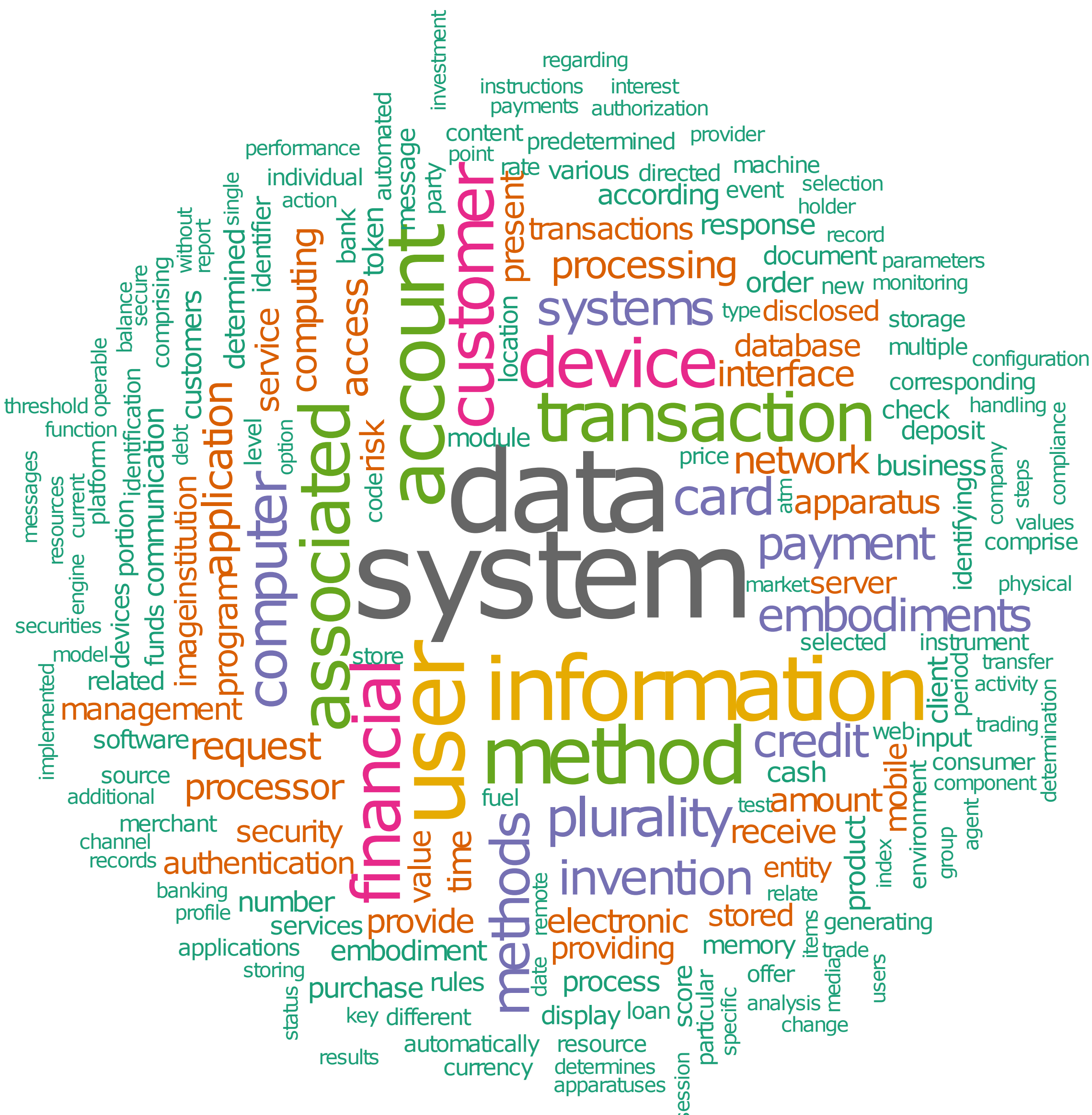


Figure 4: Share of innovative banks per county (as a percentage of branches), 1998 and 2013.

The figure plots the share of innovative banks at the county level in the years 1998 (upper plot), and 2013 (lower plot), respectively. The share of innovative banks in a given county is calculated as the number of branches operated by banks with at least one patent application 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)*.

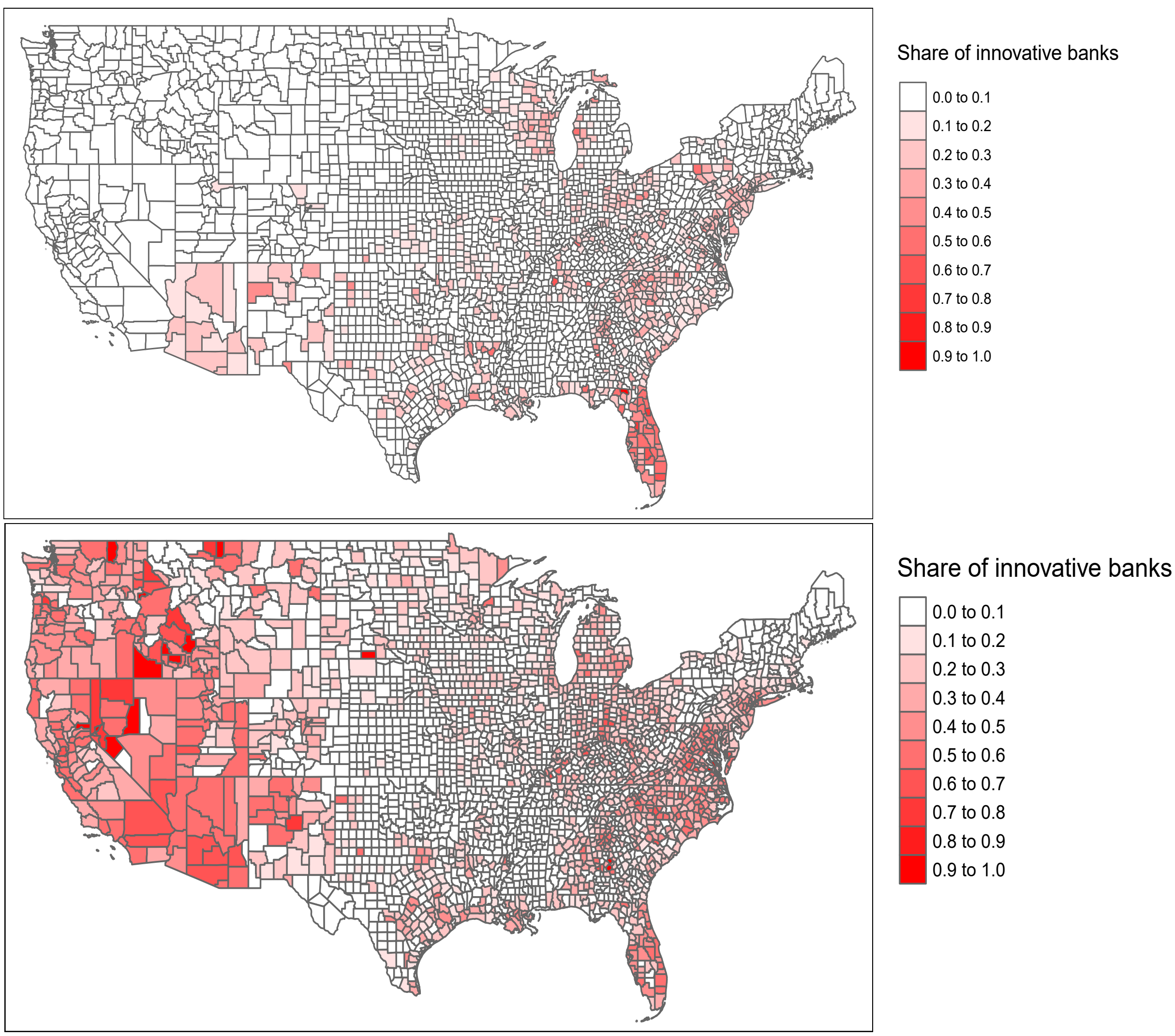


Table I: Summary statistics.

This table provides summary statistics for the panel of innovating U.S. banks from 1997 to 2016. In Panel A, observations are provided at the patent-year level, in Panel B at the bank-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 banks for 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. The growth in small business lending is constructed from Community Reinvestment Act (CRA) loan originations data available for the period of 1996 to 2016 collected by the FFIEC at the subsidiary bank level. The variable definitions and data sources are given in Appendix I.

	Mean	Median	SD
Panel A: Innovation proxies			
Patents	12.493	2	31.481
Financial Patents	2.046	0	4.155
Non-Financial Patents	10.447	2	29.277
ATM	1.801	0	5.503
Online/Mobile Banking	2.513	0	8.115
Operations/IT	5.136	1	17.821
Financial Product Innovations	0.702	0	1.904
Credit Risk Processing	0.864	0	2.178
Portfolio Selection & Trading	1.129	0	2.255
Examiner Leniency	0.089	0.080	0.160
Citations	2.567	1	5.691
Long-Term Citations	31.835	10	68.501
Short-Term Citations	15.047	6	27.414
Citation-Weighted Patents	4.006	0.194	26.699
Panel B: HMDA/CRA variables			
Mortgage Growth	0.269	0.162	0.808
Borrower Income	133.653	83.167	223.116
Loan Size to Income	1.830	1.840	1.370
Women Applicants	0.230	0.233	0.105
Minorities Applicants	0.078	0.038	0.110
Loan Acceptance Rate	-0.557	-0.563	0.184
No of Loan Applications	371.719	69.000	1467.845
Deposit Growth	0.046	0.026	0.225
Small Business Loan Growth	0.067	0.031	0.902
Panel C: Bank characteristics			
Log of Total Assets	16.178	16.101	2.553
Deposits/Total Assets	0.709	0.747	0.170
Equity Ratio	0.103	0.088	0.064
ROA	1.073	1.120	1.690
Total Loans/Total Assets	0.606	0.646	0.197
Noninterest Income/Total Income	0.647	0.342	1.113
Total Mortgages/Total Assets	0.115	0.646	0.684
Panel D: MSA characteristics			
No of Doctoral Degrees	265.917	19.000	741.442

Table II: Effect of bank innovation on deposit growth.

This table provides panel-estimations of banks' deposit growth by bank-county-year on banks' innovation from 1997 to 2016. The sample is constructed from all banks 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 year-end Call Reports. All regressions include both county*year fixed effects as well as bank fixed effects. The variable definitions and data sources are given in Appendix I. $ln(variable)$ denotes the logarithmized version of a count variable defined as $ln(variable + 1)$. Standard errors are clustered at the bank-level. 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 (1)	OLS (2)	IV (3)	OLS (4)
ln(Patents)		**-0.0051**	**0.1452*** **	
		(0.476)	**(0.002)**	
ln(No of Doctoral Degrees)	0.1083***			
	(0.000)			
ln(ATM)				0.1099***
				(0.000)
ln(Online/Mobile Banking)				0.0136
				(0.146)
ln(Financial Product Innovation)				-0.2276***
				(0.000)
ln(Credit Risk Processing)				-0.0680***
				(0.000)
ln(Operations/IT)				0.0997***
				(0.000)
ln(Portfolio Selection & Trading)				-0.0740***
				(0.000)
Mortgages/Total Assets	0.1952***	0.1409**	0.1461**	1.3857***
	(0.005)	(0.027)	(0.022)	(0.000)
Total Assets	-0.2480***	-0.0600***	-0.0055	-0.0494
	(0.000)	(0.007)	(0.836)	(0.174)
Total Deposits/Total Assets	1.1229***	-0.0351	-0.1402*	-1.5531***
	(0.000)	(0.603)	(0.075)	(0.000)
Equity Ratio	-0.4976	-0.7651**	-0.9169***	-0.7295
	(0.357)	(0.011)	(0.005)	(0.139)
ROA	0.0453**	-0.0032	-0.0120	0.0228
	(0.018)	(0.797)	(0.355)	(0.350)
Total Loans/Total Assets	0.0000***	0.0000***	0.0000**	0.0000
	(0.000)	(0.000)	(0.045)	(0.226)
Noninterest Income/Total Income	-0.0289	0.0656*	0.0708*	0.1357***
	(0.513)	(0.075)	(0.054)	(0.007)
Bank fixed effects	YES	YES	YES	YES
County*year fixed effects	YES	YES	YES	YES
Bank clustered standard errors	YES	YES	YES	YES
Kleibergen-Paap weak identification test			284.866	
Observations	18,757	18,757	18,757	26,324
R^2	0.3656	0.0062		0.0986

Table III: Effect of bank innovation on mortgage growth.

This table provides panel-estimations of banks' mortgage growth by bank-county-year on banks' innovation from 1997 to 2016. The sample is constructed from all banks 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 (not reported) control variables. Lender controls are retrieved from banks' Call Reports from the previous 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. All regressions include both county*year fixed effects as well as bank fixed effects. The variable definitions and data sources are given in Appendix I. $ln(variable)$ denotes the logarithmized version of a count variable defined as $ln(variable + 1)$. Standard errors are clustered at the bank-level. 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 (1)	OLS (2)	IV (3)	OLS (4)
ln(Patents)		**0.0557*** (0.000)**	**0.4007*** (0.000)**	
ln(No of Doctoral Degrees)	0.2388*** (0.000)			
ln(ATM)				0.1797*** (0.000)
ln(Online/Mobile Banking)				0.1342*** (0.000)
ln(Financial Product Innovation)				-0.3407*** (0.000)
ln(Credit Risk)				-0.0079 (0.285)
ln(Operations/IT)				0.0169** (0.013)
ln(Portfolio Selection & Trading)				0.0473*** (0.000)
Mortgages/Total Assets	-0.5430*** (0.000)	1.1211*** (0.000)	1.5014*** (0.000)	1.1400*** (0.000)
Total Assets	-0.0937*** (0.001)	-0.3688*** (0.000)	-0.3738*** (0.000)	-0.2718*** (0.000)
Total Deposits/Total Assets	0.9272*** (0.000)	-1.6279*** (0.000)	-2.0795*** (0.000)	-2.9003*** (0.000)
Equity Ratio	-3.0974*** (0.000)	0.4684*** (0.004)	1.4299*** (0.000)	1.6544*** (0.000)
ROA	-0.3671*** (0.000)	-0.0580*** (0.000)	0.0749*** (0.000)	-0.0358*** (0.009)
Total Loans/Total Assets	-1.6171*** (0.000)	-2.3937*** (0.000)	-1.7388*** (0.000)	-1.6706*** (0.000)
Noninterest Income/Total Income	-0.1590*** (0.000)	-0.0302 (0.351)	0.0077 (0.805)	0.0371 (0.253)
Borrower controls	YES	YES	YES	YES
Bank fixed effects	YES	YES	YES	YES
County*year fixed effects	YES	YES	YES	YES
Bank clustered standard errors	YES	YES	YES	YES
Kleibergen-Paap weak identification test			1,478.041	
Observations	89,441	89,441	89,441	89,441
R^2	0.2084	0.0719		0.1204

Table IV: Effect of bank innovation on small business lending.

This table provides panel-estimations of banks' small business loan growth by bank-county-year on banks' innovation from 1997 to 2016. The sample is constructed from all banks 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 banks' Call Reports from the previous year. The growth in small business lending is constructed from Community Reinvestment Act (CRA) loan originations data available for the period of 1996 to 2016 collected by the FFIEC at the subsidiary bank level. All regressions include both county*year fixed effects as well as bank fixed effects. The variable definitions and data sources are given in Appendix I. $ln(variable)$ denotes the logarithmized version of a count variable defined as $ln(variable + 1)$. Standard errors are clustered at the bank-level. 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: Small Business Loan Growth	First Stage (1)	OLS (2)	IV (3)	OLS (4)
ln(Patents)		**-0.0288*** (0.000)**	**1.4736*** (0.000)**	
ln(No of Doctoral Degrees)	0.0436*** (0.000)			
ln(ATM)				-0.0246*** (0.001)
ln(Online/Mobile Banking)				-0.0348*** (0.000)
ln(Financial Product Innovation)				0.0424*** (0.000)
ln(Credit Risk)				0.0598*** (0.000)
ln(Operations/IT)				0.0887*** (0.000)
ln(Portfolio Selection) & Trading				-0.1373*** (0.000)
Mortgages/Total Assets	-0.0075*** (0.000)	-0.0071*** (0.000)	0.0032*** (0.000)	0.0000*** (0.000)
Total Assets	0.8977*** (0.000)	0.4779*** (0.000)	-0.8460*** (0.000)	0.4253*** (0.000)
Total Deposits/Total Assets	0.9201*** (0.000)	0.7653*** (0.000)	-0.5742*** (0.000)	0.6528*** (0.000)
Equity Ratio	-1.3374*** (0.000)	0.8895*** (0.000)	2.5255*** (0.000)	0.9551*** (0.000)
ROA	-0.0305*** (0.000)	0.0308*** (0.000)	0.0767*** (0.000)	0.0299*** (0.000)
Total Loans/Total Assets	0.3522*** (0.000)	0.9117*** (0.000)	0.3411*** (0.000)	1.0879*** (0.000)
Noninterest Income/Total Income	0.5749*** (0.000)	0.1486*** (0.000)	-0.6867*** (0.000)	0.1578*** (0.000)
Bank fixed effects	YES	YES	YES	YES
County*year fixed effects	YES	YES	YES	YES
Bank clustered standard errors	YES	YES	YES	YES
Kleibergen-Paap weak identification test			339.345	
Observations	126,264	126,264	126,264	126,264
R^2	0.2749	0.0286		0.035

Table V: The effect of bank innovation on local and nonlocal mortgage and small business lending.

This table provides panel-estimations of banks' mortgage loan (Panel A) and small business loan growth (Panel B) by bank-county-year on banks' innovation from 1997 to 2016 for local and non-local markets. We define local markets as those in which a bank has at least one branch. The sample is constructed from all banks 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 banks' Call Reports from the previous 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. The growth in small business lending is constructed from Community Reinvestment Act (CRA) loan originations data available for the period of 1996 to 2016 collected by the FFIEC at the subsidiary bank level. All regressions include both county*year fixed effects as well as bank fixed effects. The variable definitions and data sources are given in Appendix I. $ln(variable)$ denotes the logarithmized version of a count variable defined as $ln(variable + 1)$. Standard errors are clustered at the bank-level. 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:		Panel A: Mortgage Growth		Panel B: Small Business Loan Growth	
		OLS	IV	OLS	IV
		(1)	(2)	(3)	(4)
Local					
	ln(Patents)	**-0.0264****	**0.6481*****	**-0.0239**	**-1.0995**
		(0.050)	**(0.000)**	**(0.460)**	**(0.371)**
	Bank controls	YES	YES	YES	YES
	Borrower controls	YES	YES		
	Bank fixed effects	YES	YES	YES	YES
	County*year fixed effects	YES	YES	YES	YES
	Bank clustered standard errors	YES	YES	YES	YES
	Kleibergen-Paap weak identification test		323.226		4.296
	Observations	17,659	17,659	9,162	9,162
	R^2	0.1130		0.0099	
		OLS	IV	OLS	IV
		(5)	(6)	(7)	(8)
Nonlocal					
	ln(Patents)	**0.1064*****	**0.5227*****	**-0.0666*****	**2.8940*****
		(0.000)	**(0.000)**	**(0.000)**	**(0.000)**
	Borrower controls	YES	YES		
	Bank controls	YES	YES	YES	YES
	Bank fixed effects	YES	YES	YES	YES
	County*year fixed effects	YES	YES	YES	YES
	Bank clustered standard errors	YES	YES	YES	YES
	Kleibergen-Paap weak identification test		407,212		183.890
	Observations	59,459	59,459	104,240	104,240
	R^2	0.0893		0.0354	

Table VI: Additional analyses.

This table provides the results of several additional analyses of innovative banks' outcome variable. Column (1) presents IV panel-estimations of the natural logarithm of the number of loan applications per bank 1997 to 2016. Column (2) provides panel-estimations of banks' loan acceptance rate on bank innovation. Column (3) gives IV panel-estimations of banks' growth in interest expenses to deposits. Column (4) reports bank-year panel estimations of banks' charge-off ratios on bank innovation. The sample is constructed from all banks for 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 (only columns (1) and (2)) control variables (not reported). Lender controls are retrieved from banks' Call Reports from the previous year. Borrower controls are retrieved from the HMDA database and display average borrower income, loan size-to-income ratio, percent women applicants, percent minority applicants. Regressions (1) and (2) include both county*year fixed effects as well as bank fixed effects. The variable definitions and data sources are given in Appendix I. $ln(variable)$ denotes the logarithmized version of a count variable defined as $ln(variable + 1)$. Standard errors are clustered at the bank-level. 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:	No of Loan Applications	Loan Acceptance Rate	Interest Expenses/ Deposits	Charge-off ratio
	IV	IV	IV	IV
	(1)	(2)	(3)	(4)
ln(Patents)	**0.0981*** **	**0.6969*** **	**-0.3170***	**-0.1523**
	(0.000)	**(0.000)**	**(0.088)**	**(0.532)**
Mortgages/Total Assets	1.6881***	2.4442***	0.1144***	-0.0674**
	(0.000)	(0.000)	(0.000)	(0.031)
Total Assets	0.4370***	-0.5771***	-0.2913***	0.0570
	(0.000)	(0.000)	(0.000)	(0.542)
Total Deposits/Total Assets	-0.1360	-1.1287***	-1.1508***	1.5894**
	(0.195)	(0.000)	(0.001)	(0.017)
Equity Ratio	-4.6546***	1.6343***	-0.9631	-1.2437
	(0.000)	(0.000)	(0.251)	(0.462)
Total Loans/Total Assets	0.3619***	-0.4798***	0.0000	0.0000
	(0.000)	(0.000)	(0.101)	(0.952)
ROA	-0.0844***	0.2152***	0.0405*	-0.0629
	(0.000)	(0.000)	(0.062)	(0.347)
Noninterest Income/Total Income	0.3231***	0.1539***	0.0526	-0.3447**
	(0.000)	(0.000)	(0.508)	(0.011)
Level of analysis	Bank-county-year	Bank-county-year	Bank-year	Bank-year
Borrower controls	YES	YES	NO	NO
Bank fixed effects	YES	YES	YES	YES
County*year fixed effects	YES	YES	NO	NO
Bank-clustered standard errors	YES	YES	YES	YES
Kleibergen-Paap weak identification test (F statistic)	1470.607	1466.430	5.840	6.440
Anderson-Rubin weak identification test (p value)	0.000	0.000	0.064	0.000
Observations	89,759	89,346	334	341

Table VII: The effect of bank innovation in counties with a disproportionately young/old population.

This table provides separate panel-estimations of banks' growth in deposits, mortgage loans, and small business loan growth by bank-county-year on bank innovation from 1997 to 2016 for counties with a disproportionately young (columns (1) to (3)) and old population (columns (4) to (6)). We build our first subsample of counties with a disproportionately young population by only keeping those observations from our full sample that come from U.S. counties in which the population in the age group of 19-39 years makes up at least 25% of the respective counties' overall population. In a similar fashion, we define the subsample of counties with a disproportionately old population by requiring the observations to come from counties in which more than 25% of the population are 65 years old or older. The sample is constructed from all banks 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 banks' Call Reports from the previous 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. The growth in small business lending is constructed from Community Reinvestment Act (CRA) loan originations data available for the period of 1996 to 2016 collected by the FFIEC at the subsidiary bank level. All regressions include both county*year fixed effects as well as bank fixed effects. The variable definitions and data sources are given in Appendix I. $ln(variable)$ denotes the logarithmized version of a count variable defined as $ln(variable + 1)$. Standard errors are clustered at the bank-level. 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	Mortgage Growth	Small Business Lending	Deposit Growth	Mortgage Growth	Small Business Lending
Sample:	Young (1)	Young (2)	Young (3)	Old (4)	Old (5)	Old (6)
ln(Patents)	**0.1640***** **(0.009)**	**0.4107***** **(0.000)**	**0.9374***** **(0.000)**	**0.7777** **(0.347)**	**0.4775** **(0.113)**	**0.9256*** **(0.065)**
Borrower controls	NO	YES	NO	NO	YES	NO
Bank controls	YES	YES	YES	YES	YES	YES
Bank fixed effects	YES	YES	YES	YES	YES	YES
County*year fixed effects	YES	YES	YES	YES	YES	YES
Bank-clustered standard errors	YES	YES	YES	YES	YES	YES
Kleibergen-Paap weak ident. test (F statistic)	228.734	799.604	214.935	228.734	21.332	7.262
Observations	10,945	42,087	48,615	676	6,308	4,136

Table VIII: Bank innovation and local aggregate effects.

This tables provides panel-estimations of local aggregate bank outcomes (Panel A), local bank competition (Panel B), and local real effects (Panel C) on the share of branches of innovating banks in a county relative to all bank branches in the respective county from 1997 to 2016. Panel A comprises banks' aggregate deposit growth (column (1)), aggregate branch growth (column (2)), aggregate mortgage growth (column (3)), and aggregate small business loan (SBL) growth (column (4)). Columns (5) to (7) 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 (5) shows the results of this regression for our full sample, columns (6) and (7) show the results of regressions based on two subsamples that contain only observations in counties with a low share of innovating banks (column (6); share of innovating banks less than 5%), and counties with a high share of innovating banks (column (7); share of innovating banks higher than 50%), respectively. Columns (8) to (10) present panel-estimations of GDP growth per county (column (8)), income growth per county (column (9)), and employee growth (column (10)) per county on the share of innovative bank branches in that respective county. We use county and year fixed effects and include additional 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.

	Panel A: Local Aggregate Bank Outcomes				Panel B: Local Bank Competition			Panel C: Local Real Effects		
Dependent variable:	Deposit Growth	Branch Growth	Mortgage Growth	SBL Growth	HHI	HHI	HHI	GDP Growth	Income Growth	Employee Growth
Sample:	Full	Full	Full	Full	Full	Low Share	High Share	Full	Full	Full
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Share of innovating banks	**0.0071**	**0.0171*** **	**0.2831** **	**0.2094*** **	**0.0162** **	**-0.0155** **	**0.1808*** **	**0.0151*** **	**0.0057*** **	**0.0074*** **
	(0.363)	**(0.001)**	**(0.033)**	**(0.005)**	**(0.023)**	**(0.045)**	**(0.002)**	**(0.005)**	**(0.006)**	**(0.015)**
County controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
County fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	55,014	55,014	55,014	54,953	55,014	46,210	2,037	45,846	55,014	54,993
R^2	0.0828	0.086	0.3106	0.0335	0.9598	0.9633	0.9658	0.121	0.162	0.1508

Table IX: Robustness checks.

This table provides robustness checks controlling for different effects on Deposit Growth (Panel A), Mortgage Growth (Panel B), and Small Business Loan Growth (Panel C). Each estimation includes year*county fixed effects, bank fixed effects, bank controls and in Panel B also borrower controls. Coefficients for our control variables 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) presents the results of our baseline panel regressions that additionally include the lagged level of the respective dependent variable as a further control to underline the validity of our IV approach. Row (3) considers standard errors clustered by county. Row (4) excludes the financial crisis from 2007 to 2009. In row (5) we use the variable Citations, which represents the total number of citations per patent that a bank 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)). In row (8), counties with both a high share of young and old population are excluded. Row (9) excludes states that were deregulated after 1990. In rows (10) and (11) we exclude the innovating bank's state or county headquarter, respectively. In row (12), we additionally control for banks' headquarter county fixed effects. In addition, we repeat our estimations in row (1) and control further for banks' headquarter county fixed effects (row (13)). Silicon Valley is well known as the center for high technology and innovation in California. Therefore, in row (14) we exclude the State of California in our estimations. Row (15) excludes the State of New York as the state with the highest number of average bank patent applications. 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:	Panel A: Deposit Growth			Panel B: Mortgage Growth			Panel C: Small Business Loan Growth		
		Innovation coeff.	p-value	obs.	Innovation coeff.	p-value	obs.	Innovation coeff.	p-value	obs.
1	Examiner Leniency	0.5621***	(0.000)	24,045	1.9019***	(0.000)	79,557	1.7575***	(0.000)	119,176
2	Including lagged levels of dep. variable	0.1287***	(0.004)	18,756	0.3366***	(0.000)	89,429	0.5607***	(0.000)	126,264
3	Clustered County SE	0.1452***	(0.002)	18,757	0.4007***	(0.000)	89,441	1.4736***	(0.000)	126,264
4	Excluding financial crisis	0.0939**	(0.043)	14,600	0.8228***	(0.000)	66,017	1.3536***	(0.000)	107,159
5	Citations in year t	0.2103***	(0.000)	13,348	0.5698***	(0.000)	75,767	1.0490***	(0.000)	126,264
6	Long-term Citations	0.2275***	(0.001)	13,348	0.2389***	(0.000)	75,767	0.5599***	(0.000)	126,264
7	Short-term Citations	0.1279***	(0.000)	13,348	0.3915***	(0.000)	75,767	0.4892***	(0.000)	126,264
8	Excluding counties with high share of young/old population	0.1375***	(0.010)	6,924	0.4765***	(0.000)	43,046	6.7539***	(0.000)	71,239
9	Excluding states deregulated after 1990	0.1981***	(0.000)	14,970	0.4870***	(0.000)	73,822	1.3900***	(0.000)	123,104
10	Excluding innovating banks' state headquarter	0.1451***	(0.001)	15,773	0.4222***	(0.000)	83,356	1.4766***	(0.000)	120,246
11	Excluding innovating banks' county headquarter	0.1590***	(0.000)	18,600	0.4002***	(0.000)	89,261	1.4755***	(0.000)	126,080
12	Including banks' headquarter fixed effects	0.0752*	(0.088)	18,110	0.3457***	(0.000)	89,441	0.9057***	(0.000)	126,264
13	Examiner Leniency & banks' HQ county fixed effects	0.5253***	(0.000)	23,336	2.0644***	(0.000)	78,708	0.6812***	(0.000)	116,706
14	Excluding the State of California	0.1651***	(0.002)	16,925	0.3886***	(0.000)	86,116	0.5778***	(0.000)	122,996
15	Excluding the State of New York	0.1445***	(0.005)	14,130	0.7338***	(0.000)	60,502	1.2719***	(0.000)	78,745

Internet Appendix for
“Financial Technology and Local Lending”

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

IA.1 Sample Bank Patents

This section shows examples of patent applications in each of our six patent categories. For example, Figure IA.1 presents an example of an ATM-related bank patent. More specifically, this patent describes a cash recycler that is configured to allow deposited money to be dispensed in a withdrawal transaction. Also, the currency recycler provides provisional credit for deposits of coinage and checks. Moreover, Figure IA.2 presents an example of a bank's patent on online/mobile banking. In this case, the patent filed describes a system and method that can be utilized to choose, set up, and manage an online account at a financial institution. The system allows for the automating of key aspects of an account opening process for customers. Patents in the "Operations/IT" category like the one depicted in Figure IA.3 are more general in nature, with their use not being restricted to online/mboile banking, and usually constitute improvements in information technology that can be used in different business areas of a bank. Next, the category "Financial Product Innovations" contains all patents that propose new financial contracts, or more generally, financial products. In essence, this category captures all innovations that would have been referred to as "financial innovations" before the onset of digitalization and financial technology. Figure IA.4 exhibits an example for such a financial innovation: JP Morgan Chase Bank's patent US 7.634,435 B2 for a "Diversified Fixed Income Product And Method For Creating And Marketing Same". Patents in the "Credit Risk Processing" category like the one shown in Figure IA.5 are defined by their sole use in credit risk management and loan management. Finally, innovations related to a bank's portfolio management, portfolio optimization, or trading in general are summarized in the category "Portfolio Management And Trading" for which Figure IA.6 highlights an example patent.

Figure IA.1: Sample Patent "ATM" category (US 8,756,158 B2)

The figure shows the first page of Fifth Third Bank's patent US 8,756,158 B2 for a "Currency Recycler" which is classified as an "ATM" patent in our sample. Patent data are retrieved from the *U.S. Patent and Trademark Office (USPTO)*.

US008756158B2

(12) **United States Patent**
Colvin et al.

(10) **Patent No.:** **US 8,756,158 B2**
(45) **Date of Patent:** **Jun. 17, 2014**

(54) **CURRENCY RECYCLER**

(75) Inventors: **Randy Colvin**, Hebron, OH (US); **Robert Norman**, Sunbury, OH (US); **Jeffrey Siekman**, Loveland, OH (US)

(73) Assignee: **Fifth Third Bank**, Cincinnati, OH (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 0 days.

(21) Appl. No.: **13/618,601**

(22) Filed: **Sep. 14, 2012**

(65) **Prior Publication Data**

US 2013/0218754 A1 Aug. 22, 2013

Related U.S. Application Data

(60) Provisional application No. 61/535,098, filed on Sep. 15, 2011.

(51) **Int. Cl.**
G06Q 40/00 (2012.01)

(52) **U.S. Cl.**
USPC **705/43**; 705/39

(58) **Field of Classification Search**
CPC G06Q 20/1085; G06Q 19/20; G07F 19/20
USPC 705/42, 43, 39
See application file for complete search history.

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(57) **ABSTRACT**

A cash recycler that is configured to allow deposited money to be dispensed (recycled) in a withdrawal transaction. In one embodiment, multiple currency recyclers could be used at multiple stores of a retail establishment and collectively work from one pending balance. Embodiments are also contemplated in which multiple accounts at one recycler location. In some cases, the currency recycler provides provisional credit for deposits of coinage and checks. In some cases, transactions made on the currency recycler could be settled to any financial institution.

9 Claims, 36 Drawing Sheets

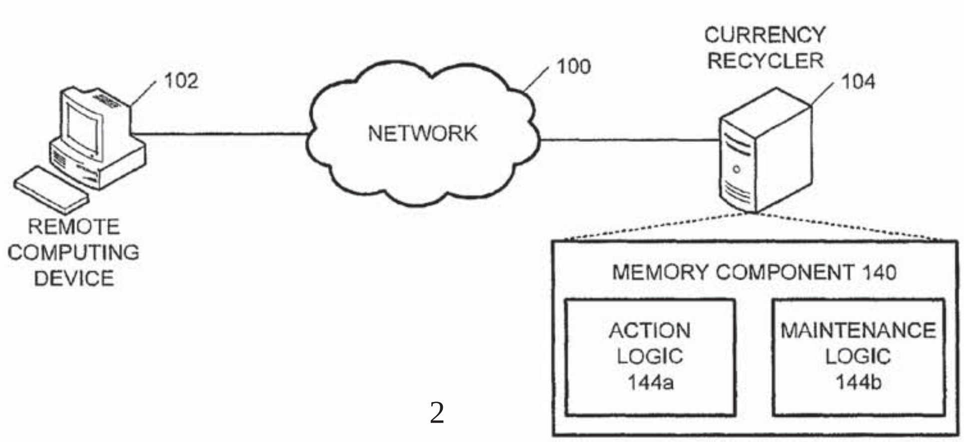

Figure IA.2: Sample Patent “Online/Mobile banking” category (US 7.620,580 B1)

The figure shows the first page of Branch Banking & Trust Company’s patent US US 7.620,580 B1 for a “Method For Online Account Opening” which is classified as an “Online/Mobile banking” patent in our sample. Patent data are retrieved from the *U.S. Patent and Trademark Office (USPTO)*.

US007620580B1

(12) **United States Patent**
Rose et al.

(10) **Patent No.: US 7,620,580 B1**
(45) **Date of Patent: Nov. 17, 2009**

(54) **METHOD FOR ONLINE ACCOUNT OPENING**

(75) Inventors: **Teresa Rose**, Raleigh, NC (US); **Patricia Kinney**, Cary, NC (US); **Barbara Whorf**, Raleigh, NC (US); **Paal Kaperdal**, Raleigh, NC (US); **Douglas Joel Zickafoose**, Raleigh, NC (US)

(73) Assignee: **Branch Banking & Trust Company**, Raleigh, NC (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 0 days.

(21) Appl. No.: **12/183,341**

(22) Filed: **Jul. 31, 2008**

(51) **Int. Cl.**
G06Q 40/00 (2006.01)

(52) **U.S. Cl.** **705/35**; 705/30

(58) **Field of Classification Search** 705/10–44
See application file for complete search history.

(56) **References Cited**

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Primary Examiner—Frantzy Poinvil
(74) *Attorney, Agent, or Firm*—Duane Morris LLP

(57) **ABSTRACT**

A system and method that can be utilized to choose, set up, open, and/or manage an online account at a financial institution. The system and method allows for the automating of key aspects of an account opening process for customers such as tailoring the presentation of information to the online customer based at least in part on the customer’s input, performing suitability checks for the customer based on online products chosen by the customer, presenting cross-sell products to the customer based on information known by the financial institution or currently received from the customer, and allowing a pending customer to complete the online application procedure in the absence of a confirmed identification of the online customer.

29 Claims, 20 Drawing Sheets

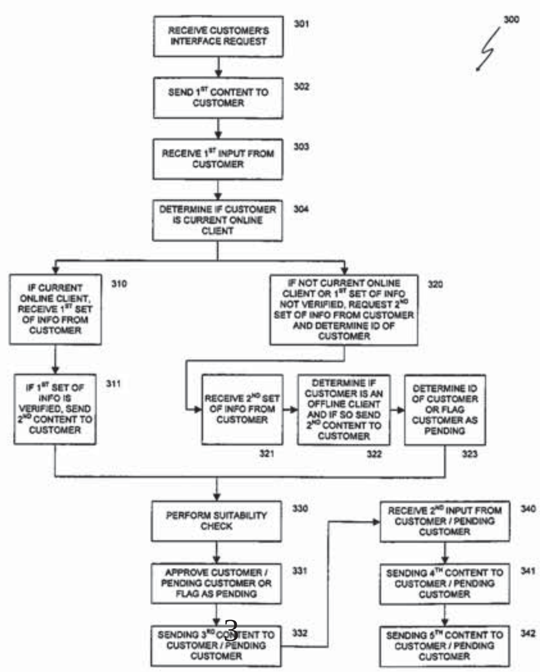

Figure IA.3: Sample Patent “Operations/IT” category (US 7,224,786 B2)

The figure shows the first page of Capital One Financial Corporation’s patent US 7,224,786 B2 for a “System And Method For Detecting Unauthorized Access Using A Voice Signature” which is classified as an “Operations/IT” patent in our sample. Patent data are retrieved from the *U.S. Patent and Trademark Office (USPTO)*.

US007224786B2

(12) **United States Patent**
Daugherty et al.

(10) **Patent No.:** **US 7,224,786 B2**
(45) **Date of Patent:** **May 29, 2007**

(54) **SYSTEM AND METHOD FOR DETECTING UNAUTHORIZED ACCESS USING A VOICE SIGNATURE**

(75) Inventors: **Joel D. Daugherty**, Richmond, VA (US); **William D. Hornsby**, Richmond, VA (US)

(73) Assignee: **Capital One Financial Corporation**, McLean, VA (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 137 days.

(21) Appl. No.: **10/659,899**

(22) Filed: **Sep. 11, 2003**

(65) **Prior Publication Data**

US 2005/0060157 A1 Mar. 17, 2005

(51) **Int. Cl.**
H04M 17/00 (2006.01)

(52) **U.S. Cl.** **379/145**; 379/114.14; 379/88.19; 704/273

(58) **Field of Classification Search** 379/145, 379/201.01, 88.19, 114.14; 704/273, 246
See application file for complete search history.

(56) **References Cited**

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Primary Examiner—Fan Tsang
Assistant Examiner—Olisa Anwah
(74) *Attorney, Agent, or Firm*—Hunton & Williams LLP

(57) **ABSTRACT**

A method for detecting unauthorized access is provided. The method includes receiving a voice input associated with a request to access an account. A request voice signature corresponding to the voice input associated with the request is generated. An authorized voice signature corresponding to the account is retrieved. The request voice signature corresponding to the voice input is compared with the authorized voice signature corresponding to the account. Unauthorized access is detected in response to the comparison.

13 Claims, 5 Drawing Sheets

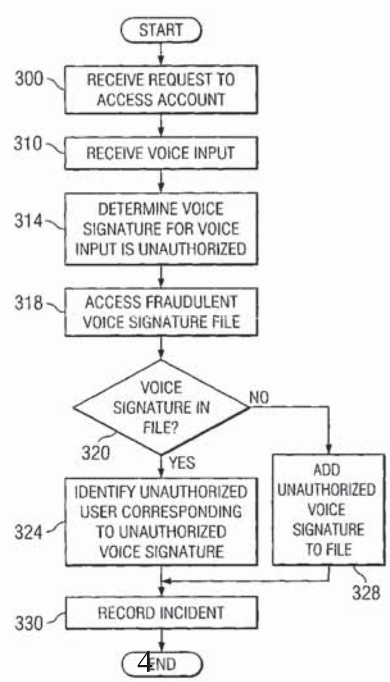

Figure IA.4: Sample Patent "Financial Product Innovation" category (US 7.634,435 B2)

The figure shows the first page of JP Morgan Chase Bank's patent US 7.634,435 B2 for a "Diversified Fixed Income Product And Method For Creating And Marketing Same" which is classified as a "Financial Product Innnovation" in our sample. Patent data are retrieved from the *U.S. Patent and Trademark Office (USPTO)*.

US007634435B2

(12) **United States Patent**
Davidovitch et al.

(10) **Patent No.: US 7,634,435 B2**
(45) **Date of Patent: Dec. 15, 2009**

(54) **DIVERSIFIED FIXED INCOME PRODUCT AND METHOD FOR CREATING AND MARKETING SAME**

(75) Inventors: **Jeffrey Davidovitch**, Brooklyn, NY (US); **Chad S. Parson**, Mount Vernon, NY (US); **Kevin E. Sprouse**, St. Louis, MO (US)

(73) Assignee: **JP Morgan Chase Bank**, New York, NY (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 1156 days.

(21) Appl. No.: **10/638,019**

(22) Filed: **Aug. 8, 2003**

(65) **Prior Publication Data**

US 2004/0230507 A1 Nov. 18, 2004

Related U.S. Application Data

(60) Provisional application No. 60/470,179, filed on May 13, 2003.

(51) **Int. Cl.**
G06Q 40/00 (2006.01)

(52) **U.S. Cl.** .... **705/35**; 705/36 R; 705/37

(58) **Field of Classification Search** .... 705/35, 705/36 R, 37
See application file for complete search history.

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Primary Examiner—Ella Colbert
Assistant Examiner—Samica L Norman
(74) *Attorney, Agent, or Firm*—Lowenstein Sandler PC

(57) **ABSTRACT**

A method of creating, registering and marketing to the public fixed income beneficial interests entitling the owners to fractional ownership of a pool of assets that pay income. The method involves selecting and acquiring from the secondary market the pool of assets, forming a trust to hold the pool of assets, creating beneficial interests in the trust, smoothing the flow of income from the assets, registering the beneficial interests for sale to the public pursuant the Securities Act of 1983, and marketing the interests. The assets can be selected to provide substantially constant payments and to return substantially par value at maturity. An automated system useful in implementing the method is described.

31 Claims, 3 Drawing Sheets

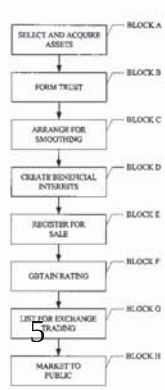

Figure IA.5: Sample Patent "Credit Risk Processing" category (US 8,156,025 B1)

The figure shows the first page of National City Bank's patent US 8,156,025 B1 for "Computer-Implemented Systems And Methods For Student Loan Application Processing" which is classified as a "Credit Risk Processing" patent in our sample. Patent data are retrieved from the *U.S. Patent and Trademark Office (USPTO)*.

US008156025B1

(12) **United States Patent**
Gymer et al.

(10) **Patent No.:** **US 8,156,025 B1**
(45) **Date of Patent:** **Apr. 10, 2012**

(54) **COMPUTER-IMPLEMENTED SYSTEMS AND METHODS FOR STUDENT LOAN APPLICATION PROCESSING**

(75) Inventors: **Matthew J. Gymer**, Bratenahl Village, OH (US); **Kevin Lawrence O'Toole**, Avon Lake, OH (US)

(73) Assignee: **National City Bank**, Cleveland, OH (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 0 days.

(21) Appl. No.: **12/269,305**

(22) Filed: **Nov. 12, 2008**

Related U.S. Application Data

(60) Provisional application No. 61/100,978, filed on Sep. 29, 2008.

(51) **Int. Cl.**
G06Q 40/00 (2006.01)

(52) **U.S. Cl.** **705/35**; 705/38

(58) **Field of Classification Search** 705/35, 705/38
See application file for complete search history.

(56) **References Cited**

U.S. PATENT DOCUMENTS

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Primary Examiner — Shahid Merchant
(74) *Attorney, Agent, or Firm* — Jones Day

(57) **ABSTRACT**

Computer-implemented systems and methods are provided for applying for student loans. A system can include graphical user interfaces for providing a series of questions to a user which relate to the applying of the student loans. At least a majority of the questions are provided to the user without reference to any specific student loan application. The responses are used to populate multiple different student loan applications.

27 Claims, 33 Drawing Sheets

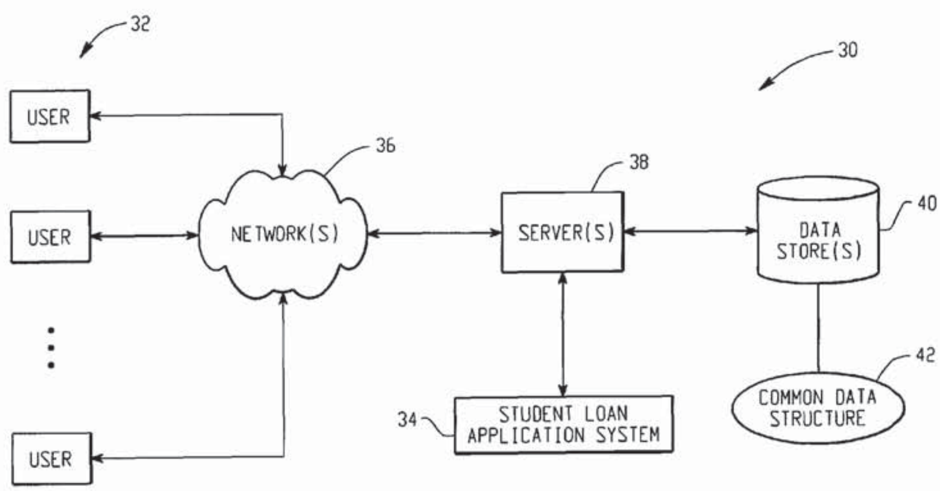

Figure IA.6: Sample Patent "Portfolio Management And Trading" category (US 7.461,021 B2)

The figure shows the first page of AMG National Trust Bank's US 7.461,021 B2 for a "Method of ascertaining an efficient frontier for tax-sensitive investors" which is classified as a "Portfolio Management And Trading" patent in our sample. Patent data are retrieved from the *U.S. Patent and Trademark Office (USPTO)*.

US007461021B2

(12) **United States Patent**
Bergmann et al.

(10) **Patent No.:** **US 7,461,021 B2**
(45) **Date of Patent:** **Dec. 2, 2008**

(54) **METHOD OF ASCERTAINING AN EFFICIENT FRONTIER FOR TAX-SENSITIVE INVESTORS**

(75) Inventors: **Michael D. Bergmann**, Bow Mar, CO (US); **Daniel Yoo**, Aurora, CO (US)

(73) Assignee: **AMG National Trust Bank**, Englewood, CO (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 1228 days.

(21) Appl. No.: **09/995,178**

(22) Filed: **Nov. 27, 2001**

(65) **Prior Publication Data**

US 2002/0143682 A1 Oct. 3, 2002

Related U.S. Application Data

(60) Provisional application No. 60/253,918, filed on Nov. 29, 2000.

(51) **Int. Cl.**
G06Q 40/00 (2006.01)

(52) **U.S. Cl.** **705/36**; 705/400; 705/35

(58) **Field of Classification Search** .... 705/36 R, 705/36 T, 400, 35
See application file for complete search history.

(56) **References Cited**

U.S. PATENT DOCUMENTS

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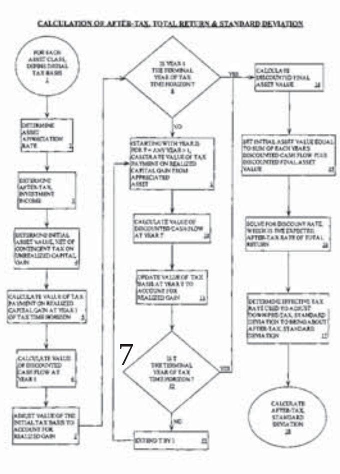
Primary Examiner—Harish T. Dass
(74) *Attorney, Agent, or Firm*—Gregory W. O'Connor

(57) **ABSTRACT**

There are computerized processes for financial planning for individuals and groups whose financial portfolio would be subject to tax on certain events. But these processes do not take into account these taxes when optimizing investment decisions, since taxes levied on investment outcomes, typically on income and realized capital gains, may have an important impact on net portfolio results. This invention is a method for transforming the usual pretax information for calculation of an efficient frontier, unique to an investor's portfolio, in such a manner that any portfolio on the calculated frontier is efficient after incorporating the effect of taxes on the risk and expected return of each asset class permitted in the investor's portfolio. This invention addresses how this may be done and how certain facets of the process may be incorporated into a computer program or system so as to provide convenience to the potential user.

8 Claims, 3 Drawing Sheets



IA.2 Alternative Identification: Patent Examiner Leniency

As we describe in the main text of our paper, our primary identification strategy employs a proxy for human capital near a bank's headquarter to employ the innovation output of a bank. We now 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 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.[1]

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:

[1] 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.

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

and

$$U_{p,t} = \frac{Grants_{u,t} - 1}{Applications_{u,t} - 1} \tag{IA.2}$$

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 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

$$\begin{aligned} Innovation_{i,l,t} &= \alpha_1 Examiner\ Leniency_{i,t} + \alpha_2 \mathbf{x}_{1,i,l,t-1} + \alpha_3 \mathbf{x}_{2,j,t-1} \\ &+ \gamma_i + \eta_t * \lambda_k + \varepsilon_{i,b,j,k,l,t}. \end{aligned} \tag{IA.3}$$

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.

The results given in Table IA.I support the findings reported in the main section of our paper. Using *Examiner Leniency* as an alternative instrument variable yields qualitatively and quantitatively similar results for our three outcome variables (growth in deposits, mortgage loans, and small business loans) as in our main analysis. Our second IV is a powerful predictor of banks' granted patents in the first stage of each regression with the Kleibergen-Paap statistic being well above 200 in all three estimations. Most importantly, however, the second stages of these three regressions strongly support our main findings that bank innovation helps bank to take in more deposits and extend credit supply.

IA.3 Additional Robustness Checks

In this section, we report detailed results from selected robustness checks summarized in the main part of our paper. To start, in Table IA.II, we substitute our main explanatory variable *Patents* by the variable *Citations* which captures the average number of citations per patent that a bank applies for in a given year. Our main findings remain unchanged.

In our main analysis, we show results of our IV regressions using the full sample of bank-county-year observations. However, even though we saturate our regressions with county*time fixed effects, one could argue that our instrument variable *Human Capital* could still be influenced by local demand effects. To control for any residual confounding local demand effects, we perform two additional robustness checks in which we repeat our main regression analyses of the growth in local deposits, mortgage loans, and small business loans in which we exclude those states (counties) in which the banks' headquarters are located. In other words, we repeat our main analyses using only those observations for counties in which the headquarter bank of a bank branch is located *outside* the respective state (county). In this way, local effects that influence our instrument variable should not simultaneously influence local deposit supply and credit demand. The results

of these regressions are shown in Tables IA.III and IA.IV. As can be seen from both tables, our conclusions reported in the main section of our paper remain valid.

Table IA.I: Alternative Identification - Examiner Leniency

This table provides panel-estimations of banks' deposit growth in columns (1) to (3), mortgage growth in columns (4) to (6), and small business loan growth in columns (7) to (9), respectively, by bank-county-year on bank innovation from 2002 to 2016. We instrument for the (log + 1) number of patents by constructing the variable *Examiner Leniency* that proxies for the average leniency of the patent office examiner in charge of a bank's patent application. The sample is constructed from all banks 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 Report from the previous 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. Regressions (1) to (9) include both county*year fixed effects as well as bank fixed effects. The variable definitions and data sources are given in Appendix I. $ln(variable)$ denotes the logarithmized version of a count variable defined as $ln(variable+1)$. Standard errors are clustered at the bank-level. 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			Mortgage Growth			Small Business Loan Growth		
	First Stage	OLS	IV	First Stage	OLS	IV	First Stage	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ln(Patents)		**0.1022***** **(0.000)**	**0.5621***** **(0.000)**		**0.0816***** **(0.000)**	**1.9019***** **(0.000)**		**-0.0351***** **(0.000)**	**1.7575***** **(0.000)**
Examiner Leniency	0.1750*** (0.000)			0.2450*** (0.000)			0.1850*** (0.000)		
Mortgages/Total Assets	-0.5382*** (0.000)	0.7702*** (0.000)	1.0342*** (0.000)	-1.0447*** (0.000)	1.4022*** (0.000)	3.1813*** (0.000)	-0.0069*** (0.000)	-0.0072*** (0.000)	0.0050*** (0.000)
Total Assets	-0.6008*** (0.000)	-0.2280*** (0.000)	0.0402 (0.588)	0.1669*** (0.000)	-0.4716*** (0.000)	-0.9525*** (0.000)	1.0375*** (0.000)	0.5397*** (0.000)	-1.2617*** (0.000)
Total Deposits/Total Assets	-0.9558*** (0.000)	-1.0045*** (0.000)	-0.6619*** (0.000)	0.6876*** (0.000)	-2.3297*** (0.000)	-4.2846*** (0.000)	1.0145*** (0.000)	0.7774*** (0.000)	-0.9758*** (0.000)
Equity Ratio	-0.4025 (0.440)	2.9759*** (0.000)	3.0520*** (0.000)	7.1901*** (0.000)	-0.4625 (0.182)	-12.7196*** (0.000)	-0.5012*** (0.000)	0.6621*** (0.000)	1.6902*** (0.000)
ROA	-0.1686*** (0.000)	0.0265 (0.305)	0.0993*** (0.001)	-0.3323*** (0.000)	-0.1267*** (0.000)	0.4398*** (0.000)	-0.0238*** (0.000)	0.0293*** (0.000)	0.0775*** (0.000)
Total Loans/Total Assets	0.0000*** (0.000)	0.0000 (0.138)	0.0000*** (0.000)	-0.8513*** (0.000)	-2.6528*** (0.000)	-0.5363** (0.030)	0.4372*** (0.000)	0.8683*** (0.000)	0.1277 (0.163)
Noninterest Income/Total Income	-0.1984*** (0.000)	0.0501 (0.467)	0.1769* (0.071)	0.3329*** (0.000)	0.0761** (0.023)	-0.3298*** (0.000)	0.5207*** (0.000)	0.1419*** (0.000)	-0.7495*** (0.000)
Borrower controls	NO	NO	NO	YES	YES	YES	NO	NO	NO
Bank fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
County*year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank clustered standard errors	YES	YES	YES	YES	YES	YES	YES	YES	YES
Kleibergen-Paap weak identification test			146.092			523.694			467.312
Observations	24,045	24,045	24,045	79,557	79,557	79,557	119,176	119,176	119,176
R^2	0.2722	0.0479		0.1435	0.1022		0.267	0.0302	

Table IA.II: Innovation Quality - Patent Citations.

This table provides panel-estimations of banks' deposit growth in columns (1) to (3), mortgage growth in columns (4) to (6), and small business loan growth in columns (7) to (9), respectively, by bank-county-year on bank innovation from 2002 to 2016. We proxy for bank innovation by using our variable *Citations* which captures the average number of citations per patent that a bank applies for in a given year. The sample is constructed from all banks 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 Report from the previous 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. Regressions (1) to (9) include both county*year fixed effects as well as bank fixed effects. The variable definitions and data sources are given in Appendix I. $ln(variable)$ denotes the logarithmized version of a count variable defined as $ln(variable + 1)$. Standard errors are clustered at the bank-level. 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			Mortgage Growth			Small Business Loan Growth		
	First Stage (1)	OLS (2)	IV (3)	First Stage (4)	OLS (5)	IV (6)	First Stage (7)	OLS (8)	IV (9)
ln(Patents)		**0.0195*** (0.000)**	**0.2103*** (0.000)**		**-0.0433*** (0.000)**	**0.5698*** (0.000)**		**0.0161*** (0.000)**	**1.049*** (0.000)**
ln(No of Doctoral degrees)	0.0901*** (0.000)			0.2168*** (0.000)			0.0612*** (0.000)		
Bank controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Borrower controls	NO	NO	NO	YES	YES	YES	NO	NO	NO
Bank fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
County*year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank clustered standard errors	YES	YES	YES	YES	YES	YES	YES	YES	YES
Kleibergen-Paap weak identification test			102.050			723.004			502.049
Observations	13,348	13,348	13,348	75,767	75,767	75,767	126,264	126,264	126,264
R^2	0.1905	0.0118		0.3333	0.1204		0.1629	0.0286	

Table IA.III: Exclusion of banks' headquarter states.

This table provides panel-estimations of banks' deposit growth in columns (1) and (2), mortgage growth in columns (3) and (4), and small business loan growth in columns (5) and (6), respectively, by bank-county-year on banks' innovation from 1997 to 2016 for branches excluding the banks' headquarter states. The sample is constructed from all banks 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 year-end Call Reports, 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. Regressions (1) to (6) include both county*year fixed effects as well as bank fixed effects. All accounting data are collected in U.S. Dollar. The variable definitions and data sources are given in Appendix I. $ln(variable)$ denotes the logarithmized version of a count variable defined as $ln(variable + 1)$. Standard errors are clustered at the bank-level. 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		Small Business Loan Growth	
	First Stage (1)	IV (2)	First Stage (3)	IV (4)	First Stage (5)	IV (6)
ln(Patents)		**0.1451*** (0.001)**		**0.4222*** (0.000)**		**1.4766*** (0.000)**
ln(No of Doctoral Degrees)	0.1947*** (0.000)		0.0000*** (0.000)		0.0426*** (0.000)	
Mortgages/Total Assets	-0.0875 (0.489)	0.3151*** (0.005)	-0.5951*** (0.000)	1.5433*** (0.000)	-0.0079*** (0.000)	0.0035*** (0.000)
Total Assets	-0.2987*** (0.000)	-0.0328 (0.231)	-0.0513* (0.097)	-0.4212*** (0.000)	0.9084*** (0.000)	-0.8320*** (0.000)
Total Deposits/Total Assets	0.4830** (0.018)	-0.1048 (0.311)	1.1754*** (0.000)	-2.2025*** (0.000)	0.9772*** (0.000)	-0.6157*** (0.000)
Equity Ratio	-1.6309** (0.015)	-1.1978*** (0.001)	-3.3613*** (0.000)	1.4860*** (0.000)	-1.1753*** (0.000)	2.4729*** (0.000)
ROA	0.0361* (0.092)	-0.0133 (0.318)	-0.4254*** (0.000)	0.0999*** (0.000)	-0.0291*** (0.000)	0.0749*** (0.000)
Total Loans/Total Assets	0.0000*** (0.000)	0.0000 (0.145)	-1.4252*** (0.000)	-1.8728*** (0.000)	0.4333*** (0.000)	0.2495*** (0.003)
Noninterest Income/Total Income	0.0154 (0.756)	0.0081 (0.803)	-0.0948** (0.018)	-0.0026 (0.938)	0.5684*** (0.000)	-0.6826*** (0.000)
Borrower controls	NO	NO	YES	YES	NO	NO
Bank fixed effects	YES	YES	YES	YES	YES	YES
County*year fixed effects	YES	YES	YES	YES	YES	YES
Bank clustered standard errors	YES	YES	YES	YES	YES	YES
Kleibergen-Paap weak identification test		124.787		1278.745		296.876
Observations	15,773	15,773	83,356	83,356	120,246	120,246
R^2	0.3945		0.2208		0.2706	

Table IA.IV: Exclusion of banks' headquarter counties.

This table provides panel-estimations of banks' deposit growth in columns (1) and (2), mortgage growth in columns (3) and (4), and small business loan growth in columns (5) and (6), respectively, by bank-county-year on banks' innovation from 1997 to 2016 for branches excluding the banks' headquarter counties. The sample is constructed from all banks 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 year-end Call Reports, 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. Regressions (1) to (6) include both county*year fixed effects as well as bank fixed effects. All accounting data are collected in U.S. Dollar. The variable definitions and data sources are given in Appendix I. $ln(variable)$ denotes the logarithmized version of a count variable defined as $ln(variable + 1)$. Standard errors are clustered at the bank-level. 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		Small Business Loan Growth	
	First Stage (1)	IV (2)	First Stage (3)	IV (4)	First Stage (5)	IV (6)
ln(Patents)		**0.1590*** **		**0.4002*** **		**1.4755*** **
		(0.000)		**(0.000)**		**(0.000)**
ln(No of Doctoral Degrees)	0.1091***		0.0000***		0.0436***	
	(0.000)		(0.000)		(0.000)	
Mortgages/Total Assets	0.2057***	0.1670***	-0.5490***	1.5041***	-0.0076***	0.0032***
	(0.003)	(0.008)	(0.000)	(0.000)	(0.000)	(0.000)
Total Assets	-0.2589***	-0.0138	-0.0934***	-0.3740***	0.9000***	-0.8483***
	(0.000)	(0.602)	(0.001)	(0.000)	(0.000)	(0.000)
Total Deposits/Total Assets	1.1219***	-0.1242*	0.9410***	-2.0729***	0.9250***	-0.5806***
	(0.000)	(0.095)	(0.000)	(0.000)	(0.000)	(0.000)
Equity Ratio	-0.4529	-1.0235***	-0.3719***	0.0755***	-1.3127***	2.4928***
	(0.416)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
ROA	0.0435**	-0.0136	-1.6072***	-1.7617***	-0.0304***	0.0765***
	(0.026)	(0.275)	(0.000)	(0.000)	(0.000)	(0.000)
Total Loans/Total Assets	0.0000***	0.0000**	-3.0940***	1.4306***	0.3571***	0.3336***
	(0.000)	(0.015)	(0.000)	(0.000)	(0.000)	(0.000)
Noninterest Income/Total Income	-0.0331	0.0412	-0.1533***	0.0088	0.5754***	-0.6882***
	(0.468)	(0.228)	(0.000)	(0.780)	(0.000)	(0.000)
Borrower controls	NO	NO	YES	YES	NO	NO
Bank fixed effects	YES	YES	YES	YES	YES	YES
County*year fixed effects	YES	YES	YES	YES	YES	YES
Bank clustered standard errors	YES	YES	YES	YES	YES	YES
Kleibergen-Paap weak identification test		273.560		2,047.609		339.777
Observations	18,600	18,600	89,261	89,261	126,080	126,080
R^2	0.3675		0.2093		0.2749	