The Anatomy of Banks' IT Investments: Drivers and Implications *

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Abstract

This paper relies on administrative data to study determinants and implications of US banks' Information Technology (IT) investments, which have increased six-fold over two decades. Large and small banks had similar IT expenses a decade ago. Since then, large banks sharply increased their spending, especially those which were more exposed to competition from fintech lenders. Other local-level and bank-level factors, such as county income and bank income sources, also contribute to explain the heterogeneity in IT investments. Analysis of the mortgage market reveals that fintechs' lending behavior is more similar to that of non-bank financial intermediaries rather than IT-savvy banks, suggesting that factors other than technology are responsible for the differences between banks and other lenders. However, both IT-savvy banks and fintech lend to lower income borrowers, pointing towards benefits for financial inclusion from higher IT adoption. Banks' IT investments are also shown to matter for the responsiveness of bank lending to monetary policy.

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"We see ourselves as a technology company with a banking license"

Michael Corbat (2014), Citibank (CEO)

"We want to be a tech company with a banking license"

Ralph Hamers (2017), ING (CEO)

"JPMorgan plots 'astonishing' $12bn tech spend to beat fintech"

Financial Times, January 15, 2022

1 Introduction

The use of technology is transforming the financial services industry. Fintech lenders are gaining market share possibly thanks to their ability to make it easier and faster to approve loans. For example, fintech lenders' share of US mortgage lending rose from 3 percent in 2010 to 15 percent in 2021.[1] At the same time traditional banks have also vowed to become more technology-centered players.[2] However, it is unclear to which extent these proclaims have resulted in sizeable information technology (IT) investments. And, if banks have indeed been adopting IT at a sustained pace, which factors explain such investments? What is the role of competition from fintech players? Most importantly, what are the consequences of such large IT investments?

To answer these questions, we construct a novel measure of banks' information technology (IT) spending using textual analysis of publicly available regulatory filings (Call Reports) for US banks. This measure, building on work by Kovner et al. (2014), improves on previous ones which mainly relied on indirect measurement or survey data. It allows us to study the drivers of IT spending, as well as to investigate whether banks that invest more on IT display a different lending behavior than other banks in terms of riskiness, inclusiveness, and transmission of monetary policy to credit.

Using the novel data we first confirm that banks' IT expenses have increased tremendously. In nominal terms, they are six times larger in 2021 than in 2001 and three times larger than in 2011, despite the rapidly declining price of computing power (Moore's law). Banks' assets and overall expenses have grown at a much slower pace during the last decade. However, the increase in IT adoption masks signif-

[1] See subsection 3.3.

[2] For instance, see quotes reported by https://www.sepaforcorporates.com/payments-news-2/technology-companies-what-big-banks-spend-say-about-tech/ and the Financial Times article *JPMorgan plots 'astonishing' $12bn tech spend to beat fintech* https://www.ft.com/content/e543adf0-8c62-4a2c-b2d9-01fdb2f595cc (January 15, 2022).

icant heterogeneity. While the share of IT to overall expenses a decade ago was similar for large banks relative to their counterparts, the former adopted IT at a much faster pace than small banks in the post Global Financial Crisis (GFC) era. This striking fact suggests the presence of novel economies of scale in the use of IT in banking, as gains from collecting and analyzing data may be more beneficial for larger firms, which in fact have been investing more in data science and artificial intelligence (Babina et al., 2021).

We explore the role of a host of factors in explaining cross-sectional differences in banks' IT expenditure, focusing on the average spending over the last five year before the COVID pandemic. Anecdotal evidence suggests that competition from fintech lenders propels traditional financial intermediaries to increase their investments in technology to keep up with their digital counterparts. We test this claim more formally by exploiting variation in banks' exposure to early fintech mortgage lenders (companies that allow for a fully online mortgage origination) and indeed find that banks more exposed to fintech competition invest more in IT. This relationship is particularly strong for larger banks, consistent with the idea that IT adoption benefits larger lenders disproportionately more. We also adopt an instrumental variable strategy which relies on the fact that Michigan is one of the US states with the largest fintech shares (mostly because it is home to the main mortgage fintech lender, Rocket Mortgage). IV estimates indicate a causal effect of competition from fintech in spurring IT adoption. This causal impact could operate in two ways: either banks may want to become more similar to fintechs in order to compete with them directly and IT expenses are instrumental to this goal, or banks more exposed to fintechs may have realized earlier the power of digitalization in finance and thus invested more, even if IT is used primarily for different purposes. The mortgage-level analysis discussed later in this section suggests the latter explanation is more important than the former.

Heterogeneity in local characteristics can impact banks' incentives to invest in IT because of demand and supply factors. For instance, the presence of borrowers or depositors that do not enjoy visiting physical branches is a demand factor that may encourage banks' investments in online banking. The availability of IT savvy workers is a supply factor that may facilitate the adoption of new software or hardware. We analyze the role of local characteristics in driving banks' IT adoption by projecting each county-level variable at the bank-level using banks' local footprint as captured by the deposits across US counties. We find that banks which operate in poorer counties adopt more IT, consistent with evidence–discussed below–that less well-off costumers are more likely to rely on fintech or high IT banks for mortgages. The availability of human capital can also be a key input for firms' technology adoption. We measure local human capital as the share of adults with tertiary education and with the availability of STEM or math-savvy graduates within a county. While none of these variables explains IT adoption of the average bank, the share of STEM graduates at local universities is correlated with IT adoption of smaller banks, suggesting it is more difficult for them to hire specialized personnel from different parts of the country. Perhaps surprisingly, we do not detect any significant role for neither broadband access nor local bank concentration. Counties' racial composition is also uncorrelated with banks' IT expenses.

Banks' business model and funding structure contribute to explaining IT adoption. For instance, banks that earn a larger share of income from non-interest sources and that have more deposits also spend more on IT, suggesting that IT can help banks better serve their depositors and earn fees on different products. Less profitable banks also spend more on IT, suggesting this can be a way to seek cost saving opportunities. For instance, improvements in IT capabilities can diminish the need for physical branches or personnel. Consistently, we find that banks that have reduced the number of branches more in the last 5 years, also spend more on IT. This is particularly true for large banks.

We then turn to the consequences of bank IT adoption. The lending behavior of banks that invest more in IT may be different than other banks, along dimensions that are relevant for risk-taking, financial inclusion, and monetary policy transmission. For instance, IT may matter for risk taking because it improves lenders' screening and monitoring abilities, or makes banks generally more resilient (Berg et al., 2019; Pierri and Timmer, 2022; Kwan et al., 2021). IT investments may be beneficial for financial inclusion insofar they facilitate clients online interaction with banks, allowing for greater reach (serving rural areas or poorer neighborhoods) and possibly reducing discrimination based on income or race. We also analyze whether banks with high IT spending behave more like fintech lenders relative to low IT banks and nonbanks. This is useful to understand whether any financial stability or financial inclusion gains stemming from the rise of fintech are related more to the technological features of these players or other factors such as their regulatory oversight (fintechs are generally nonbank financial intermediaries that do not take deposits and are not subject to bank regulations) or funding structures.

To conduct our analysis, we combine information on banks' IT spending from Call Reports with loan level data from the Home Mortgage Disclosure Act (HMDA) database. The mortgage market is an ideal laboratory to study the consequences of bank IT adoption. While fintechs also have a presence in the small business credit markets (Beaumont et al., 2021; Gopal and Schnabl, 2022), the role of fintech lenders is particularly striking in the mortgage market as the largest mortgage lender is a fintech company.

We confirm that fintech players' lending behavior is different from that of banks across multiple dimensions. Fintech lenders originate mortgages with higher loan-to-value (LTV) and debt servicing-to-income ratio (DTI) at origination. These mortgages are used to buy properties of smaller value, they are given to borrowers with lower income, and who are less likely to be non-Hispanic Whites.[3] These mortgages are also more likely to be used for refinancing purposes.[4] However, all these characteristics (with the exception of the likelihood of refinancing) are shared by other non-fintech nonbanks mortgage originators. This indicates that differences in factors other than IT capabilities, such as regulatory requirements or funding structures, are likely to be more important in explaining fintech behavior relative to banks.

Furthermore, we show that banks that spend more in IT are more similar to other banks than to fintech players. For instance, they originate mortgages of similar amount, interest rates, and LTVs. However, like fintechs, they also lend more to borrowers with lower income and those with higher DTI ratios. Quantitatively, the difference in borrowers' income between high IT banks and others is about a third of the difference between other banks and fintechs: banks that spend more on IT are still more similar to other banks (than to fintechs) in this dimension as well. IT may benefit lower income borrowers if they prefer to interface with banks through online channels rather than visiting a physical bank branch, where people with more wealth and education may be treated better and that may be located closer to richer areas. Technology may also improve the access to credit of less well-off households if it improves banks' ability (or willingness) to manage risk. Application-level regressions reveal that high IT banks are more likely to receive applications from lower income applicants and also more likely to accept them, conditional on applying. This suggests that both explanations for the role of IT in favoring low income borrowers may be relevant.

This collection of findings suggests that a more IT intense banking sector may foster financial inclusion of lower income borrowers, however at the potential cost of higher risk because of an increased DTI ratio. We do not find, instead, an improved access to credit for minority borrowers at high IT banks,

[3] A caveat regarding the last result is that the race variable is missing for a large share of fintech loans (30% versus 11% on average).

[4] These results are robust to the inclusion of county of the property times year fixed effects, other loan characteristics, and originator size.

which instead lend less to these borrowers.

The extent to which monetary policy impacts credit provision is fundamental for central banks' ability to stabilize prices and the economy. Changes in the financial intermediaries' landscape, such as the growing importance of fintechs or shadow banking, can affect such transmission (Chakraborty et al., 2018; Elliott et al., 2022; Agarwal et al., 2022). Bank's IT investments can also change their responsiveness to monetary policy shocks. On the one hand, IT may help banks acquire market power (for instance by offering better online services to borrowers) as documented in other industries and thus have less elastic demand. In this case, the amount of credit they provide would be less sensitive to changes in interest rates. On the other hand, IT may increase the sensitivity of the supply schedule to the external cost of funding, for instance by diminishing the weight of other variable costs of providing a loan, such as administrative expenses, thanks to greater operational efficiency.

To provide evidence in this regard, we exploit high-frequency monetary policy shocks around monetary policy decisions. We show that unexpected monetary policy tightening by the Federal Reserve leads to a decline in total loans on US banks balance sheets and increases the interest rates banks charge, consistent with a negative supply shock induced by contractionary monetary policy. We show that the effect of unexpected monetary policy tightening on credit is weaker and the effect on lending interest rates is stronger for banks that adopted IT more heavily. This can be rationalized by high IT banks facing lower demand elasticity. We perform an additional robustness analysis, relying on syndicated loan-level data, which allows us to control for borrower-quarter fixed effects. This analysis reveals that the results on monetary policy, IT and lending volumes are not driven by differences in the mix of borrowers which caters to high versus low IT banks (at least in the market of corporate credit).

Taken together, these results suggest that banks IT investment reduce the transmission of monetary policy to credit but strengthens its pass-through to lending rates.

Related Literature

This paper contributes to the literature on technology adoption by banks. Berg et al. (2019) find that IT spending by banks improves their ability to monitor and screen borrowers and recent papers document that IT increases banks' resilience during crises (Branzoli et al., 2021; Kwan et al., 2021; Dadoukis et al., 2021; Pierri and Timmer, 2022).[5] Other paper have studied the impact or the determinants of different

[5] Jansen et al. (2022) show that increased data availability can lead to increases in total social welfare.

technological innovation (such as ATM, online banking, or high-speed internet) in banking (Hannan and McDowell, 1987; Berger, 2003; Bofondi and Lotti, 2006; Hernández-Murillo et al., 2010; Bostandzic and Weiss, 2019; D'Andrea and Limodio, 2019) while some recent contributions focus on the connection between IT in banking and credit to small firms or startups (He et al., 2021; Ahnert et al., 2021). We contribute by building a new measure of IT spending by US banks from regulatory filings, studying its determinants (in particular the role of fintech competition), and its connection with lending behavior and response to monetary policy shocks.

Previous literature document several benefits of fintech lending (see Berg et al. (2021) for a review). For instance, Fuster et al. (2019) find a 20 percent improvement in processing time in the context of US mortgage lending. Many studies document benefits for financial inclusion, such as fintechs lending more to underserved borrowers and communities (Erel and Liebersohn, 2020; Jagtiani et al., 2021; Dolson et al., 2021) and being less likely to discriminate against minority borrowers Howell et al. (2021); Bartlett et al. (2022). We contribute by showing that the more IT-savvy banks also lend more to poorer borrowers, although not to racial minorities. This paper is also related to work by Buchak et al. (2018), who show that the rapid rise of nonbank financial intermediaries in US mortgage origination, including fintech lenders, is mostly related to regulatory arbitrage while technological advantage is a less important factor. While our results are consistent with these findings, we also study to which extent banks that adopt more IT become more similar to fintech lenders.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 provides summary statistics and stylized facts. Section 4 analyzes the drivers of banks' IT adoption. Section 5 compares the lending behavior of banks with differential degrees of IT adoption to FinTech lenders and other non-bank financial intermediaries. Section 6 studies the role of IT adoption for monetary policy transmission. Section 7 concludes.

2 Data

Bank data and IT expenses The Call reports are quarterly regulatory filings submitted by commercial banks in the US to the Federal Deposit Insurance Corporation (FDIC). Unfortunately, banks are not specifically required to report IT investments or expenses.[6] However, banks report the top (up to) three

[6]From 2016 on, respondent can report depreciated software among their "other assets", but we do not find this asset category to be quantitative meaningful and therefore we focus on IT-related expenses.

items within non-interest expenses that are not otherwise itemized and represent at least 10 percent of the unclassified non-interest expenses.[7] We build on Kovner et al. (2014) and use textual analysis to classify these top three expense items in different categories. In particular, we classify an expense line as "IT expense" if its description contains any IT-related keyword such as "software", "computer", or "internet".[8]

Introducing and describing this measure of IT expenses is a key contribution of this paper.[9] As the revolutionary power of IT stems from being a multi-purpose technology, we study general adoption of information technology rather than specific technologies (e.g. ATMs, online banking, or Mortgage Electronic Registration Systems, as in Hannan and McDowell (1987), Hernández-Murillo et al. (2010), or Lewellen and Williams (2021)). This approach is better suited to understand how financial intermediaries are evolving as they ramp up their technological investments, while focusing on a specific technological application may lead to a narrower and more biased assessment, as each one may have a different impact.[10].

Our measure improves on previous studies by extracting information on IT spending from regulatory filings. Seminal papers have relied on survey data–in particular the ones collected by the marketing intelligence company Aberdeen (previously known as Harte Hanks)–to measure IT adoption of non-financial firms (Bloom et al., 2012; Beaudry et al., 2010). Recent papers have relied on the same approach to study IT adoption of financial intermediaries (Pierri and Timmer, 2022; Ahnert et al., 2021; Kwan et al., 2021; He et al., 2021). However, information extracted from regulatory filings is likely to be of much higher quality because of the legal obligation and resources involved in these filings. Most importantly, marketing survey data can sometimes be plagued by errors and opaque imputations. In particular, the Aberdeen data appear to be mostly imputed during the most recent survey waves and therefore are not appropriate for any bank-level analysis focused on recent years. Our measure, instead, avoids such concerns.

The main downside of our measure is that it underestimates the actual amount of IT expenses for two

[7]The expenses are reported in Schedule RI-E—Explanations 2.n 2.o, and 2.p, variables Text4464 Text4467, and Text4468 and RIAD4464, RIAD4467, and RIAD4468.

[8]The full set of keywords includes "web", "software", "it " (e.g. it services), " it ", "pc", "computer", "technology" (e.g., information technology), "internet" (e.g. internet banking), "computer", "online", "electronic banking", "tech " (e.g., tech services) , "network it", "data". These keywords were chosen after reading several thousands descriptions of banks' expense items. Figure A1 illustrate the use of some of these words over time.

[9]Additional details on data download will be posted at http://www.nicolapierri.com

[10]For instance, Lewellen and Williams (2021) and Rajan et al. (2015) document, respectively, that the Mortgage Electronic Registration Systems and the over-reliance on statistical models of defaults contributed to the build-up of financial risks before the GFC. These findings would suggest a detrimental role of information technology for financial stability. However, more recent papers show that overall IT adoption by US banks improved screening and mitigated the impact of both the GFC and the COVID crisis (Pierri and Timmer, 2022; Kwan et al., 2021)

reasons. First, some expenditures may be reported without reference to their IT content. For instance, expenses to train employees using a novel software may be simply reported as "training" expenses. Similarly, "consulting fees" or "equipment maintenance" could refer to IT consulting and equipment, but we cannot confidently classify them as IT expenses. Second, an IT-related expenditure may not be reported because it does not meet the criteria of being among the top three non-interest expenses and exceeding the minimum reporting threshold.[11] Therefore, our measure provides a lower bound for total banks' IT expenses. In fact, only a minority of banks report IT related expenses in a given year (the post 2010 average is 15 percent, while only about 5 percent of banks reported such expenses in 2001). Therefore, it is a useful measure to capture variation across institutions and over time, but comparisons with other type of expenses or income flows are much less reliable.

Other bank-level variables, such as deposits, assets, and loans, are also taken from the Call reports for the years 2000 to 2021. 2021 data are available up to the second quarter and are imputed for the rest of the year, under the assumption that, for each item, the ratio between first half and second half of the year is the same in 2021 as in other years (2021 data are not used in the formal empirical analysis).

To compare IT expenses across banks, we normalize by dividing them by either banks' assets or total non-interest expenses. Neither normalization is perfect: while assets are a more standard measure of bank size, they are a stock measure while expenses are flows. On the other hand, banks' non-interest expenses may depend on their organizational efficiency, which can be correlated with IT use itself. Luckily, the patterns documented in the paper are consistent across both normalization methods.

We compare our new measure of IT adoption with other more indirect measures that have been proposed in the literature. For instance, (Petersen, 1999; Petersen and Rajan, 2002) have argued that IT enables banks to originate more loans per employee and leads to a decline of the physical distance between borrowers and lenders. Our measure of IT expenses are indeed positively correlated with the ratio of loans on a bank's balance sheet over the number of employees, the share of out-of-state mortgages, as well as the average distance to borrowers (see Figure A2). We also find that banks that offer full online applications have a larger degree of IT adoption than those that conduct mortgage application only in person.

[11] Moreover, the fact that no IT expenses are reported, does not mean that overall IT expenses are not big enough. For instance, let us consider the case of a bank for which the five largest non-interest expenditures are, in decreasing order, "correspondent bank fees", "manager training", "vault", "software", "computers". The bank would not report any IT related expenses, if "software" plus "computers" combined are larger than the other items.

Mortgage data Home Mortgage Disclosure Act (HMDA) is a rich dataset containing lender, loan, as well as borrower level information. Importantly, HMDA contains application level data, which includes loans that were actually originated. HMDA contains lender level information like name, lender identifier (RSSD id), type of lender, and zip code of the lender. It contains loan level information such as loan amount, loan type, property type, rate spread and tract-county of loan-origination. From 2018 onwards, it also contains information such as interest rates charged, combined loan to value ratio, debt to income ratio, loan term, property value and purchaser type . Finally, HMDA contains anonymized borrower-level information like race, sex, ethnicity, and income. Our sample includes first lien, one-to-four family property type mortgage loans for purchase or refinance purposes. We focus on the years from 2007-2021.

Fintech classification, local characteristics, and additional datasets Fintech lenders are lenders with a strong online presence. Following previous literature, we classify a non-bank mortgage originator as fintech lender Buchak et al. (2018); Fuster et al. (2019); Jagtiani et al. (2021). We classify a lender in HMDA as a bank if they file a Call report. Finally, a non-bank non-fintech is referred to as a non-bank throughout the rest of the paper. We exclude credit unions[12] from the sample because of their different incentives and business models with respect to commercial banks and other originators.

County level characteristics are drawn from multiple standard data sources. Socio-demographic characteristics are taken from the 2010 US census and American Community Survey. Data on college graduates is taken from the 2018 IPEDS (Integrated Postsecondary Education Data System) survey. Income per county is provided by Internal Revenue Service. FDIC provides data on banks' deposits across the US.

Syndicated loans We obtain data on syndicated loans for large corporations from DealScan's database of large bank loans (Ivashina and Scharfstein, 2010) from 2002 to 2019. In the DealScan data, for the banks in the syndicate, there is only information on the total facility amount, and whether the banks act as participants or lead arrangers. As the individual contributions are not recorded in most of the cases, we distribute two-thirds and one-third of the total loan amount to lead arrangers and other participants, respectively, following, for example, Chodorow-Reich (2014). In particular, we follow the cleaning procedure of Bittner et al. (2021).

[12] HMDA agency code = National Credit Union Administration or if the name of the lender included the words "credit union"

We merge DealScan with the Call reports using DealScan's Lender ID and Call Report BHC ID following Chakraborty et al. (2020). We aggregate bank-level variables at the BHC-level by taking weighted averages, with assets being the relevant weights. The final dataset includes more than 105 thousands quarter-bank-borrower observations which represent the credit provided by 90 bank holding groups.

Outliers Variables are winsorized at the top 2 percent (by year) if they have a lower bound at zero (e.g., ratio of IT expenses to assets) and winsorized at bottom and top 1 percent (by year) otherwise (e.g., log assets).

3 Descriptive Patterns

3.1 IT expenses over time

Figure 1 illustrates the evolution of banks' total IT expenses compared to those of assets and non-interest expenses.[13] Up to the immediate aftermath of the GFC the three series show similar dynamics. However, from 2013 on, IT expenses increased at a much faster rate than assets, while overall non-interest expenses increased less than assets. In fact, IT expenses in 2021 were 6 times larger–in nominal terms–than in 2001, while the other items were slightly more than 3 times larger with respect to the 2001 values. This is particularly striking because the price of computation steadily decreases over time (Moore's law), suggesting an even larger divergence in real terms.

Have all banks adopted IT with the same intensity? Figure 2 illustrates that small and large banks had similar IT expenses until approximately 2010. This is in line with the finding that the availability of IT equipment was similar for banks of different sizes, during the early 2000s (Pierri and Timmer, 2022). Since the early 2010s, instead, large banks–in particular the ones in the top decile of the size distribution–have spent much more in IT than smaller ones. In fact, in the last 5 years only the largest banks have continued or increased their IT expenses, while average expenses have gone down in the other size categories.[14]

This striking fact is consistent with the presence of novel economies of scale in the use of IT in banking. These could arise–for instance–because large banks can collect significant amounts of data from

[13]The three items are normalized to be equal to 100 in 2001.

[14]These patterns are similar if we focus on a balanced panel of banks (Figure A3). The very largest banking groups have similar dynamics of IT investments over time from the rest of the top 10 percent largest banks, as shown by Figure A4 where the banks belonging to the top 30 bank groups are separated from the others.

their costumers and monetize them. This mirrors the finding that the gains from collecting and analyzing data have been accruing mostly to the ex-ante larger firms (Farboodi et al., 2022), which in fact have been investing more in data science and artificial intelligence (Babina et al., 2021).

A potential concern with these empirical patterns is that large banks may have simply started recording more and more of their non-interest expenses over time–and thus the data patterns are really caused by measurement errors. This is not the case. In fact Panel (a) of Figure 3 shows that other non-interest expenses (that is, non-interest expenses which are classified with descriptions that do not involve IT related keywords) have been declining over time, and small and large banks follow similar patterns. Moreover, Panels (b), (c), and (d) illustrate the evolution of several important bank-level characteristics and document that the patterns over time are mostly parallel between large and small banks. This evidence points towards IT specific factors driving the patterns illustrated by Figure 2.

3.2 Distribution of IT expenses and correlation with other IT related measures

Figure 4 shows the cross-sectional distribution of IT expenses as a share of non-interest expenses (patterns are extremely similar if we normalize by assets). The figure focuses on the 5 years average from 2015 to the last pre-Covid year (2019) and plots both the unconditional distributions (winsorized at the top 2 percent) and the distribution conditional on reporting some IT expenses. The former is highly skewed, partly because some IT expenditures, especially the smaller ones, are not captured.

The green dashed lines represent the overall averages, while the red lines report the average for a subset of banks that, in 2019, offer the possibility of fully online mortgage application (as reported by Buchak et al. (2018) (updated list). This is consistent with IT investments being instrumental to improve banks' online lending capabilities.

Previous literature has argued that two consequences of IT adoption in banking are the ability to originate more loans per employee and a decline of the importance of physical distance between borrowers and lenders (Petersen, 1999; Petersen and Rajan, 2002). In fact, Figure A2 focuses on 2019 data and shows that IT expenses are positively correlated with the ratio of loans on a bank's balance sheet over the number of employees (Panel a). IT expenses are also positively correlated with two measures of borrower-lender distance constructed using HMDA mortgages: the share of mortgages for properties that are in states where the bank has no branches (Panel b), and the average distance between a bank's headquarter county and the county of borrowers' properties–weighted by the size of the mortgages (Panel c). These findings are consistent with evidence that IT adoption decreases the importance of physical distance in explaining banks' response to local economic shocks (Ahnert et al., 2021).

3.3 Mortgage Markets and Fintech Shares

Figure 5 (Panel a) shows the evolution of total mortgage loan value over time. Notably, fintechs' total mortgage lending increased from 54 B$ in 2010 to 630 B$ in 2021. Interestingly, the total mortgage lending increased by 2.5 times during the period from 2018 to 2021 from 1500 B$ to 4200 B$.

Fintech lending increases by around 4 times in the same period, from 3 to 15 percent, as shown in Figure 5 (Panel b). Their share in the refinance section of the market is even higher, reaching 20 percent in 2021. This is in line with Buchak et al. (2018) who suggest that fintechs have a comparative advantage in the refinance market because (1) home purchase requires more labor as compared to refinancing and (2) banks' incentives to refinance loans on their balance sheets are lower because it directly cuts into their profits.

Figure 6 shows that in 2015, fintech shares were larger in less dense states like Nevada, Wyoming, and Texas. This is in line with Erel and Liebersohn (2020) who show that for small business lending, fintech lending occurs disproportionately in ZIP codes with fewer bank branches and lower incomes. In recent years, fintechs have quickly expanded to mortgage markets in more dense states like California and Maryland. Notably, Michigan has a high fintech share in the early years due to Rocket Mortgage, the largest lender in the US mortgage markets, having its headquarters there.

4 Determinants of IT in banking

The previous section illustrated the importance of bank size in explaining IT investments. In fact, in 2019 the correlation between log of assets and IT expenses (normalized by non interest expenses) was 0.25. In this section, we rely on cross sectional regressions to test different hypotheses on the other potential determinants. We focus on 2019 as the base year to abstract from the impact of the COVID pandemic on banks' and their incentives.

Fintech and banks' competition A sizeable literature has studied the relationship between the competitive environment and firms' incentives to innovate or adopt new technologies (Aghion et al., 2005), and this can be an important factor for banks as well (Hernández-Murillo et al., 2010; Yannelis and Zhang, 2021).

In particular, anecdotal evidence points towards fintech competition being a factor pushing banks' adoption of IT. For instance, the *Financial Times* reports in January 2022 that "*JPMorgan plots astonishing $12bn tech spend to beat fintechs*".[15] However, how banks react to digital disruption is an empirical question (Vives, 2020). To empirically investigate the connection between fintech competition and banks' IT expenditure, we exploit the fact that banks operate in different geographical markets within the US (e.g., see Buchak and Jørring (2021) for evidence that mortgage lenders compete at the local level), and fintech market shares are also unevenly distributed across the country (Buchak et al., 2018). We compute, for each county and each year since 2010, the share of mortgages originated by fintech companies (weighted by their value). We call "fintech exposure" of a bank the weighted average of fintech market shares across US counties weighted by the mortgages that the bank originated in that county. That is, given a county c, bank b, and year t, we compute:

$$ExposureFintech_{b,t} = \sum_c \frac{Mortgages_{c,b,t}}{Mortgages_{b,t}} \frac{MortgagesFintech_{c,t}}{Mortgages_{c,t}} \tag{1}$$

We then define as "early exposure to fintech", the average of $ExposureFintech_{b,t}$ from 2010 to 2015. To proxy for bank competition, instead, we measure local market concentration of deposits. That is, we calculate the HHI of deposits for each county in the US, and then we compute the bank-level exposure to concentration in banking as the weighted average of the counties' HHI, weighting each county by the deposits the bank has in that county. Results are similar if we focus on concentration of the local mortgage markets instead of deposits.

Branch consolidation A potential benefit from banks' adoption of IT is that it can partly substitute for the local presence of physical branches–for instance by helping banks interface with costumers through online channels–or more generally diminish the need of human work. We therefore measure branch consolidation with the 5-year growth rate of the number of branches with deposits from FDIC data. The growth is measured with DHS growth rates[16] from 2015 to 2019.

[15] See https://www.ft.com/content/e543adf0-8c62-4a2c-b2d9-01fdb2f595cc.

[16] The DHS growth rate is equal to $2 \times \frac{X_t - X_{t-1}}{X_t + X_{t-1}}$ (Davis et al., 1998).

Local characteristics Local characteristics of the areas where a bank operates may also impact its technological adoption in different ways. On the demand side, they may impact costumers' attitude towards technology or costs altering the benefits of adopting IT, particularly related to front-end processes. For instance, online banking interaction may be favored by borrowers with higher level of education or by those who have been traditionally less welcomed in bank branches, such as individuals with low-income or belonging to a racial minority. On the supply side, the availability of technical knowledge may make it easier for banks to adopt new technologies and may also make banks' executives more aware of their effectiveness. Availability of broadband connections may also foster IT adoption for both demand and supply factors. IT in banking may be particularly helpful in less densely populated areas of the country. Thus, we obtain county-level information of income, share of minority population (that is, everyone except for White non-Hispanic), share of adults with some tertiary education, average income, population density per sq KM, share of population with access to a broadband connection of at least 25 Mbps, share of STEM among the graduates from universities in the commuting zone, math score (75th of SAT exam) of graduates from universities in the commuting zone (see section 2 for data sources).[17] As dependent variable–IT adoption–is at the bank-level, we take the weighted average of each county-level measure by weighting each county by the banks' deposits in that county.

Bank characteristics We also include a set of controls for bank characteristics. The share of income from non-interest rate sources and the share of loans over assets proxy for a bank's business model. The share of deposits over assets and the share of equity over assets are used to measure differences in funding sources. Net income over assets, instead, measures profitability.

Empirical Specification We estimate the cross sectional linear regression:

$$IT_b = \alpha + \beta X_b + \epsilon_b \tag{2}$$

where the dependent variable IT_b represents IT expenses (normalized by assets or non-interest expenses), averaged across 2019-2015; we average across 5 years because of the lumpiness in the reporting

[17]We are not aware of granular and publicly accessible data sources about local presence of STEM graduates, thus we focus on the students graduated by nearby universities and colleges. We focus on graduates from all universities located in the commuting zone to which a county belong–rather than county itself–as universities can impact the availability of human capital in the whole local labor market (Moretti, 2004), and commuting zones are constructed exactly to capture local labor markets.

of IT expenses; we stop at 2019 to abstract from the impact of the COVID pandemic. X_b is the set of covariates described above. All variables, including the banks' geographical footprint used to construct the local characteristics variables, are lagged by 5 years, so not to be contemporaneous with the dependent variables–with the exception of log assets, because of the importance to properly control for size in explaining IT documented in section 3. Summary statistics are reported in Table A1.[18]

The results of estimating Equation 2 by OLS are reported in columns (1) and (2) of Table 1, weighting banks by their loans. Large banks adopt more IT. A doubling of size leads to an increase of IT expenses which is about half of the sample mean.

Banks which have been more exposed to fintech competition also spend more on IT. The estimated coefficient is quite large, although it is statistically different from zero only at 10% confidence level: an increase in one standard deviation of fintech exposure is associated with an increase of IT expenses which is almost 90 percent of its sample mean. Having experienced more intense competition from fintech could stimulate IT adoption for two reasons: either banks are trying to become more similar to fintechs in their lending behavior and IT expenses are instrumental to this goal, or banks more exposed to fintechs may have realized earlier the power of digitalization in banking and thus invested more even if IT is used primarily with different purposes. In section 5, we present evidence that the lending behavior of high IT banks–on most dimensions–does not become more similar to the one of fintech lenders suggesting the latter story is more likely than the former.

We do not find that bank concentration explains IT adoption. Most of local-level characteristics are also statistically insignificant, with the exception of income. Banks in areas with lower income individuals tend to adopt more IT. In section 5, we provide evidence that this may be due to low income borrowers preferring IT lenders–for instance, because in person interactions in bank branches may be unpleasant for some low-income individuals–which may explain why banks with more low-income potential borrowers spend more on IT. Surprisingly, we do not find a significant correlation with local access to broadband.

Banks with lower profits in the past also spend more on IT, perhaps because of the need to improve their cost structure. In fact, banks that reduce more the number of physical branches also invest more in IT. This is consistent with IT adoption being useful to substitute for physical presence and allow for

[18]The sample includes slightly less than 3,000 banks out of the 5,000 in the 2019 Call report: the main reasons is that we include only banks that we can merge across Call reports, FDIC, and HMDA datasets for the period 2015-2019.

cost savings. Banks with a larger share of income from non-interest sources and with more deposits also increase IT spending: this suggests that IT may be used in part for activities different than lending, such as interacting with depositors through online channels.

Given the sharp divergence of large banks' IT investments with respect to the other banks, we then augment Equation 2 by interacting all the independent variables with a dummy for whether the bank is "large", that is in the top 20 percent or 10 percent of all banks according to their assets. We report some of the resulting coefficients in Table 2, where columns 1 and 3 refers to large banks as those in the top 20 percent while columns 2 and 4 refers to large banks as those in the top 10 percent. Some interesting findings are that fintech competition fosters IT adoption especially at large banks, and that the availability of STEM graduates appears to facilitate IT adoption of small/medium banks, at least when we use non-interest expenses as a normalization. This latter finding could be explained by larger banks being more able to attract talent at the national level. Large banks that decrease the number of branches also spend more in IT, while this is not the case for smaller banks.

4.1 Instrumenting exposure to fintech competition

Banks which were more exposed to the competition of fintech mortgage originators in the early phase (2010-2015), also end up adopting more IT. This relationship could arise because of a causal impact of fintech exposure on banks' IT or because of correlated confounding factors. For instance, one concern with a causal interpretation of the results is that banks and fintech which compete in the same local markets may be both trying to cater to similar "IT loving" borrowers.

The history of the most important fintech mortgage lender in the US provides an empirical strategy to disentangle the two stories. Quicken Loans (Rocket Mortgages since 2018) was founded with the name of Rock Financial by a group of entrepreneurs led by Dan Gilbert. In 1998 the company declared the aim to move the mortgage origination process online. The first fully electronic mortgage application process was launched in 2002, enabling consumers to review and sign documents online. The company was relatively unscathed by the subprime crisis and grew very fast in the aftermath of the GFC to become the largest US mortgage originator in 2018.[19]

The company was headquartered in Michigan since its start (first in Livonia, Southfield, and Bingham, and then moved to Detroit) because it is the state where the founder was born and grew up (com-

[19]Information on the history of Rocket Mortgage is mostly taken from Wikipedia and the company's website.

pany's non-financial investments, such as direct investments in real estate or hotels, and its philanthropic efforts have also been focused on the Detroit metropolitan area). Although the majority of the company's mortgages are made online, Michigan was one of the states with the largest market share of this company–and thus of fintech in general–during the early 2010's. Michigan does not host any important financial center, nor any tech hub, so Michigan being home to the main fintech company is one of the main reasons for the large share of fintech mortgages in the state. While this home state effect may appear at odds with the ubiquity of internet access across the country, there is ample evidence that even the diffusion of internet content and digital services follows the law of gravity (Blum and Goldfarb, 2006). Figure 7 indeed reveals a positive correlation between the share of deposits that a bank has in Michigan in the 2010-2015 period and the exposure to fintech competition in the same period.[20]

We therefore re-estimate the Equation 2 by instrumenting the fintech exposure variable with the share of deposits that a bank has in Michigan (2010-2015). We include all the bank- and local-level controls. This mitigates the concern that a bank's presence in Michigan masks the exposure to different local credit market characteristics, for instance to less dense areas of the country, rather that Michigan itself. Results are presented in Table 3. The first column reports the first stage, and confirms that the correlation between the instrument and the endogenous variable is robust to the inclusion of the controls. Columns (2) and (6) report the OLS estimates. Columns (3) and (7) show that banks with a larger share of deposits in Michigan also have higher IT spending. Columns (4) and (8) present the IV estimates which indicate a positive impact of exposure to fintech competition on IT expenses. Columns (5) and (9) illustrate that the results do not depend on the inclusion of controls.

An important concern with these estimates is that the first stage t-statistics of the exogenous instrument is less than 4. Moreover, we obtain much larger IV coefficient than OLS. These two elements indicate the presence of a weak-instrument problem. Therefore, we apply weak instrument techniques following Andrews and Stock (2018). Rather than producing point estimates, these techniques aim to provide confidence intervals for the parameter of interest while taking into account the extra variability introduced by the low power of the first stage. Each point is included in the set if a certain statistical test cannot reject that value for the parameter (i.e. constructed through "test-inversion"). As it is recommended in our setting (Isaiah et al., 2018; Andrews and Stock, 2018), we construct such confidence

[20]We focus on share of deposits in Michigan because mortgage market shares may endogenously respond to fintech competition.

interval by relying on a version of the Anderson and Rubin test (Anderson and Rubin, 1949) which allows for non-homoskedastic standard errors. Table 3 reports the 90% confidence interval based on this test. Such intervals are large, as intuitively expected given the low power of the instrument. However, they all reject the null of no impact of early exposure to fintech competition on IT adoption.

In conclusion, the instrumental variable empirical strategy presented in this section points to a causal impact of exposure to fintech, although given the lack of power, we cannot confidently provide a point estimate for such effect.

5 Lending Behavior

To shed light on the potential consequences of a more technology centered financial industry, we study the differences in lending behavior between more IT intensive banks, less IT intensive banks, fintechs, and non-banks. A bank is classified as a high IT bank in a year if its IT expenses to non-interest expenses ratio, averaged over the past five years, is higher than the median for all banks in that year. Otherwise, it is classified as a low IT bank.[21] Our period of analysis includes the years between 2018 and 2021, since it was in this period that fintech lenders were established as market participants and the HMDA dataset contains richer loan-level information from 2018 on.

Mortgage-level specification We estimate the following linear regression:

$$Y_{ilzt} = \beta \text{Class}_{lt} + \gamma X^1_{izt} + \zeta X^2_{lt-1} + \delta_{zt} + \epsilon_{ilzt} \tag{3}$$

where Y_{ilzt} is a dependent variable of interest for loan i originated by lender l in county z at year t, Class_{lt} is the class of lender: low IT bank (base), high IT bank, fintech or non bank, X^1_{izt} are the loan level controls, X^2_{lt-1} are lender controls which include the (log of) total amount of mortgages issued by lender l in the previous year to proxy for the size of the lender, and δ_{zt} are county-year fixed effects. The loan level controls include product type, purchaser type loan purpose, occupancy type and hoepa status. All standard errors are clustered at the lender level.

[21] Given the skewness in the distribution of IT expenses, being any bank with positive IT investment is classified as high IT. The low IT group is larger than the high IT. The appendix report results using the continuous variable (IT expenses over non interest expenses) rather than a dummy for high IT banks, finding similar patterns. The results of this section are also similar if we normalize IT expenses by assets, but they are not reported for brevity.

Table 4 shows the results for different dependent variables including the county-year fixed effects, loan-level, and lender-level controls. (In the appendix we present results even without controls or adding additional borrower-level controls, finding in general similar patterns.) Combined loan to value ratio (LTV), monthly debt to monthly income ratio (DTI), log of loan amount, log of property value, interest rate, loan term (in months), log of income of the borrower, a dummy for whether the income of borrower is in the bottom 20% percentile, a dummy for whether at least one of the applicants is non-white or Hispanic and a dummy for whether the loan purpose is for refinancing correspond, respectively, to columns 1-10. The last four rows report the mean value of the dependent variable for the base low IT banks, the standard deviation for the same, the p value for the test that the coefficient for the high IT bank and fintech are equal and the p value for the test that the coefficient for the fintech and non banks are equal, respectively.

Column (1) shows that fintechs and non-banks have an approximately 3 percentage point higher combined loan to value ratio (LTV) as compared to low IT banks. High IT banks have a similar LTV as compared to low IT banks. As can be concluded from the second-last row in the table, fintechs and non-banks take on more LTV risk than high IT banks. Column (3) and (4) suggest that this high LTV is driven by 6% lower property values for non-banks and 10% lower property values for fintechs. Interestingly, this risk is not compensated by higher interest rates as can be seen in column (5), despite nonbanks issuing longer term mortgages column (6). Fintech lenders are also more likely to lend for refinancing purposes.

We then consider some outcomes that are relevant for financial inclusion. Column (7) shows that on an average, the mortgage borrowers of high-IT banks, fintechs and non-banks have 3% , 9% and 11% lower income respectively as compared to borrowers of low IT banks. Thus, high IT banks, like fintechs, lend to poorer borrowers although the difference with low IT banks is just a third than the difference between low IT banks and fintechs. Results are similar if we consider a dummy for borrower in the bottom quintile of income (Column 8). Column 2 reveals that lending to income with lower income translates into higher DTI. Given that the average debt to income ratio (DTI) for low IT banks is around 32.5 percent, the ratio for high-IT banks, fintechs, and non-banks is approximately 1%, 4% and 4% higher, respectively. Thus high IT banks become similar to fintechs and non-banks by catering to the lower income borrower and taking on more risk in terms of higher DTI. However, high IT banks do not take as much risk as fintechs and non-banks (second-last row).

Discrimination in mortgage markets has been an important obstacle for minority home ownership in the US and an important cause of racial wealth disparities. It is thus a concern of policy makers to promote financial inclusion of these underserved borrowers. We therefore also analyze which type of lenders cater more to minority borrowers, defined as non-white or Hispanic (see column 9). An important caveat of this analysis is that the minority variable is missing for 30% of fintech observations and 11% for other lenders. Consistent with previous literature, we find that mortgages to minority borrowers are more likely to be originated by fintech lenders. We do not find the same for high IT banks, which are less likely to lend to these borrowers.

This collection of results reveal that banks investing more on IT do *not* become much alike the fintech lenders, which instead behave very similarly to other nonbanks. in line with previous literature (Buchak et al., 2018), this points towards non-technological factors, such as differences in regulations, business models, and funding structures as being the main determinants of fintech lending. However, the results also reveal that IT investments do matter for bank lending. In particular, banks' IT investments seem to benefit financial inclusion on the income dimension, but not on the race dimension.

A potential concern with our empirical specification is that IT investments are also correlated to other bank characteristics, such as the funding or income sources (see Table A13). Therefore, we re-estimate a version of Equation 3 where we focus only on mortgages originated by banks and analyze the lending behavior of banks with different degree of IT investments, controlling for the bank-level characteristics described in section 4. We find qualitatively similar results, as reported in Table A13, which points towards IT itself, and not correlated factors, driving the differences in lending behavior between high and low IT banks.

Application-level analysis Differences in lending to borrowers with different characteristics, such as to lower income individuals, is the product of two margins: (1) application margin–more lower income borrowers and/or minorities *apply* to particular types of lenders and (2) acceptance margin - some lenders *accept* more applications of lower income borrowers and/or minorities as compared to other lenders.

Disentangling these two margins can be helpful to shed light on the mechanisms behind the results illustrated above. For instance, if high IT banks or fintech lend more to low income individuals because they are better able to provide services online and low income borrowers may find it less pleasant or inconvenient (because of distance) to use a physical branch, then we would expect the application margin to drive the results. If these lenders provide more credit to lower income individuals because of higher risk tolerance or better risk management (e.g., due to better screening or monitoring), then the acceptance margin should be more important.

We therefore re-estimate Equation 3 including all loan applications originated and not-originated (but exclude withdrawn applications) where the two dependent variables are: applicant income or minority status. Results, presented by Table 5, reveal an important role for the application margin. Controlling for the county of the property, high IT banks, fintechs, and nonbanks all receive more applications from lower income borrowers with respect to low IT bank. Fintechs and nonbanks also receive more applications from minority borrowers.

Acceptance probability To assess the importance of the acceptance margin, we estimate how the probability of accepting a mortgage application changes with borrower and lender characteristics. We rely on a linear probability model:

$$\text{Accept}_{ilzt} = \beta \text{Class}_{lt} + \text{Class}_{lt} \cdot \text{minority}_{ilzt} + \text{Class}_{lt} \cdot \text{income}_{ilzt} + \gamma X^1_{izt} + \zeta X^2_{lt-1} + \delta_{zt} + \epsilon_{ilzt} \tag{4}$$

where $Accept_{ilzt}$ is a dummy for whether the loan application i was accepted, Class_{lt} is the class of lender (high IT bank, fintech or non bank, while lot IT bank is the baseline), minority is a dummy for whether at least one of the applicants is non-white or hispanic,income is the log of income of the borrower, X^1_{izt} are the loan level controls, X^2_{lt-1} are lender controls which include the log amount of mortgages issued by lender l in the previous year to proxy for the size of the lender, and δ_{zt} are county-year fixed effects. The loan level controls include product type, purchaser type, loan purpose, occupancy type and hoepa status. All standard errors are clustered at the lender level.

Columns (1) and (2) simply check whether the unconditional acceptance rate of different lenders differs. Fintechs acceptance rate is 23 percent higher than low-IT banks after adding controls and county-year fixed effects. This could be related to the quicker processing of fintechs (Fuster et al., 2019). We then add controls for the applicant income and minority status, and their interaction with the lender type. We find that low IT banks accept more applications from high income applicants, but the reverse is true for the other lender types. Fintech and nonbanks are also more likely to accept applications from minority applicants, while banks do not. These findings indicate that the acceptance margin is important to understand why some lenders lend more than others to borrowers with certain characteristics. They also suggest that both online experience and risk tolerance/management can contribute to explain why high IT banks serve poorer borrowers than low IT banks.

6 Response to Monetary Policy

A central role of the banking system is to transmit monetary policy to the real economy. A question of paramount importance is thus whether and how such transmission would be different in a more technologically intense financial system. To provide evidence in this regard, we study how a bank's lending response to monetary policy shocks depends on a bank's past investments in IT.

There are different reasons why IT may impact the transmission of monetary policy. On the one hand, technology may increase banks' responsiveness because of supply side factors. For instance, IT can improve banks' ability to collect and analyze information and thus more promptly change prices in response to change in costs. Consistent with this "agility" hypothesis Fuster et al. (2019) document that fintechs adjust supply more elastically than other lenders in response to exogenous demand shocks, while Ahnert et al. (2021) provide similar evidence regarding credit to small firms and banks that use more IT equipment. Moreover, IT diminishes, at the margin, the operational cost of providing a loan. The marginal cost of lending is the cost of funds plus the marginal operational cost. Thus, the cost of funds may be a higher share of the marginal cost of lending for high IT banks than for low IT. Therefore, a change in interest rate would have a larger impact, in proportion, to the marginal cost of providing a loan for the high IT banks.

On the other hand, demand factors may lead to different results. IT investments are often linked to higher firm market power (Foster et al., 2022). Previous literature shows that technology allows fintech to process loans faster (Fuster et al., 2019) and provide convenience to customers, (Buchak et al., 2018). As an example of how technology may impact market power in the banking industry, IT may help banks replicate some of these gains which may induce borrowers to be more "loyal"/"sticky" and less sensitive to price changes. If high IT firms face a more inelastic demand, then a supply shift–such as the one caused by a monetary tightening–would lead to a larger change in prices and smaller in quantities with respect to low IT firms. Moreover, market power in banking is often found to decrease the transmission of monetary policy to credit (Benetton and Fantino, 2021). Therefore, how IT interact with monetary policy transmission is an empirical question.

For this empirical analysis we rely on monetary policy shocks constructed by Jarociński and Karadi (2020), who study central bank announcements and use high frequency data to disentangle the information component and the pure monetary policy shock. We aggregate such shocks at the quarterly level to match with quarterly Call report information. We use the linear projection method by Jordà (2005) and first estimate the following set of linear regressions:

$$\Delta^h \log Y_{b,t} = \delta_b + \beta^h MP_{t-1} + \gamma X_{b,t} + \epsilon_{b,t} \tag{5}$$

where $\log Y_{b,t}$ is an outcome of interest for bank's b balance sheet in quarter t and $\Delta^h \log Y_{b,t} = \log Y_{b,t+h} - \log Y_{b,t-1}$. We consider two outcomes ($Y_{b,t}$): (i) loans, which we use to approximate the quantity of credit (as in Kashyap and Stein (2000)), and (ii) interest rate on loans (interest income on loans over loans), which we use to approximate the price of credit. δ_b is a bank fixed effect, MP_{t-1} is the monetary policy shock in the quarter $t-1$, and $X_{b,t}$ is a set of time-varying controls which includes lags up to $t-3$ of the monetary policy shocks, of the information component, and of quarterly GDP growth, and a time trend. The coefficients β^h estimate the cumulative impulse response function (IRF) of a bank to a monetary policy shock.

We estimate Equation 5 by OLS, weighting banks by the average amount of loans in their balance sheet. Standard errors are double clustered at the bank and quarter level. The resulting IRF, together with 90% confidence interval, is presented by Figure 8. Figure 8 reveals that the amount of lending temporarily declines following a contractionary monetary policy shock, while the interest rate charged by banks on loans increases (although this specification has lower power). An increase in prices associated with a decline in quantity is the expected response to an increase in the cost of funding (negative supply shock).

To understand whether the impact of monetary policy is different according to a bank's IT adoption, we estimate the augmented set of regressions:

$$\Delta^h \log Y_{b,t} = \delta_b + \zeta_t + \alpha^h MP_{t-1} \cdot IT_{b,y(t-4)} + \gamma X_{b,t} + \epsilon_{b,t} \tag{6}$$

where $IT_{b,y(t-4)}$ is the bank's average IT spending in the previous 5 years normalized by non interest expenses or by assets (produce the same results). We include time (quarter) fixed effects ζ_t, to control for any time varying factors (so the variable MP_t drops). Within the set of controls $\gamma X_{b,t}$, we also include (with a one-year lag) the time varying bank-level variables discussed in section 4 equity, deposits, net income, loans normalized by assets, share of non-interest income, and log of assets to control for other time varying shocks that could impact the amount of lending or its price. For instance, banks that have experienced a negative shocks to profitability or capital may need to contract lending regardless of the monetary policy stance in order to preserve capital buffers. (IT expenses are obviously included without interaction term as well.)

The coefficients α^h, together with 90% confidence intervals, are reported by Panles (a) and (b) of Figure 9 (also in Table A2 and Table A3). The coefficients in both panels are are positive. This indicates that monetary policy shocks have a smaller contractionary impact on credit quantity for banks that spend more on IT but a larger impact on credit pricing. To visualize this heterogeneity, Panels (c) and (d) plot the estimated cumulative impulse response function to a 100 basis point unexpected monetary tightening for a bank with one half standard deviation IT adoption above and below the mean. These two banks differ by one standard deviation of IT investments. When we focus on loans (Panel c) their response function is quite different: the trough of the bank with lower IT adoption is more negative by a third with respect to the trough of the bank which invest more in IT. The two impulse response function are, instead, less different when we focus on interest earned (Panel d).[22]

As discussed above, these findings can be rationalized by high IT banks facing a less elastic demand curve, in line with previous literature arguing IT investments are connected to greater market power. (Figure A6 provides a simple graphical illustration of how the findings can be rationalized by differences in residual demand elasticity.) They also suggest that in a world where technology is more and more pervasive in the financial sector, central banks may need to react more aggressively using interest rates to impact credit growth.

An alternative interpretation of the finding that high IT bank adjust credit less than other banks is that these banks are also less financial constrained. In fact, while section 4 documents no correlation of IT with equity over assets, it also shows that IT expenses are higher for larger banks and banks with more deposits. More deposits and larger size are likely associated to more stable funding. However, if IT was just capturing differences in financial constraints and funding resilience, both loan quantity and pricing would react less to monetary policy shocks (while we find pricing reacts more). That is, if low IT banks were simply more constrained in the amount of credit they can provide after a monetary

[22] Figure A5 present the same patters as the Panels (a) and (b) of Figure 9 while normalizing IT by assets rather than non interest expenses. While the qualitative dynamics is unchanged, the magnitude of the coefficients is of course much larger as IT expenses over assets are almost two order of magnitude smaller than IT expenses over non interest expenses

contraction, but they face a downward sloping demand, then they would provide such credit at higher rate.[23] Furthermore, we augment Equation 6 by the interaction between monetary policy shocks and (lagged) deposits over assets, log assets, capital over assets, and securities over assets,[24]. As reported by Figure A7, we find qualitatively similar results (smaller in magnitude than those reported by Figure 9 but within the confidence intervals).

Syndicated Loans The exercise above indicate quantitatively important differences in the change of lending by high and low IT banks following a monetary policy shocks. This exercise has two limitations. One is that the Call reports provide information on the stock of loans on banks' balance sheet but no variable that properly captures new credit. The second is that the differences between the response to monetary policy of high and low IT banks may also by driven by differences in borrower-level (rather than bank-level) shocks. In fact, previous literature shows that monetary policy also impacts the mix of borrowers served by banks (Jiménez et al., 2014).

We therefore analyze monetary policy and its impact on syndicated loans (see section 2 for more details). We rely on the simple linear equation:[25]

$$\log credit_{f,b,t} = \delta_{f,t} + \zeta_b + \sum^{h=1,2,3} \left(\alpha^h MP_{t-h} \cdot IT_{b,y(t-4)} \right) + \gamma X b, t + \epsilon_{b,t} \tag{7}$$

where $\log credit_{f,b,t}$ is the log amount of new credit provided from bank b to borrowing firm f summed over all the new issuance in quarter t. In the most saturated version of our specification, we include borrower-quarter fixed effects $\delta_{f,t}$ to control for any time-varying borrower shocks to isolate the coefficients α^h, which reveal how monetary policy shocks impact the intensive margin of credit differently for high and low IT banks. Bank-level time varying controls, and their interaction with monetary policy, are included as in Equation 6.

Table 7 presents the estimated coefficients α^h, together with t-stats based on standard errors double clustered at bank-lender and quarter level. Columns (1) to (3) and (7) present results based on IT normalized by non interest expenses. Columns (1) to (3) add progressively finer fixed effects (bank and

[23] Such simple reasoning could be invalidated if the marginal borrower was riskier than the average borrower, so that banks focus on less risky lending when they contract lending. However, below we also show that our findings hold only controlling for borrower mix.

[24] Securities over assets is a measure of assets liquidity which has been shown to impact banks' response to monetary policy shocks (Kashyap and Stein, 2000).

[25] See for example, Elliott et al. (2022) for a similar analysis comparing non-banks to banks in response to monetary policy shocks using the DealScan data.

borrower, bank, borrower and quarter, and then bank and borrower times quarter), while column (7) adds time-varying bank controls and their interaction with monetary policy shocks. Columns (4) to (6) and (8) present the same results but normalize IT expenses by assets. The coefficients α_1 are always positive and statistically significant, indicating that credit provision of banks which spend more on IT responds less to monetary policy shocks, confirming the results on Equation 6. (α_2 is also positive but not always statistically significant, while α_3 is never statistically different from zero.)

It is also interesting that the inclusion of borrower times quarter fixed effects lead to a small decline in the coefficient of interest α_1 (e.g., see column 2 vs column 3). This suggests that the heterogeneity of borrower-level shocks faced by low and high IT banks is small, and the patterns documented by Figure 9 would not be very different if we were able to control for borrower-level shocks.

This exercise confirms the finding that high IT banks are less responsive to monetary policy shocks and that those results are not driven by differences in demand or by mismeasurement of credit flows. The downside of this exercise is that, because of data limitations, we need to focus on large corporate borrowers, which can be very different than the average corporate or household borrower in the economy. Corporate lending is often thought as being very "soft information" intensive, and thus less responsive to IT adoption; however, recent empirical evidence shows that corporate lending is also impacted by banks' technology (Pierri and Timmer, 2022; Ahnert et al., 2021; He et al., 2021).

7 Conclusions

This paper studies the drivers and consequences of bank IT adoption, using a newly created measure of IT investments from banks' regulatory filings. We find that banks have invested significantly in IT over the last decade. While large banks had a similar share of IT investment compared to their peers until the GFC, large banks have invested in IT much more aggressively than smaller banks since then. We also provide evidence that fintech competition contributed to banks' IT investments, especially for the large banks.

Turning to the consequences of banks' IT adoption, generally, we do not find that banks that invested more in IT became more similar to fintechs in terms of their lending behavior. Instead, fintechs and other non-bank lenders are very similar to each other in selecting borrowers, suggesting that factors other than IT adoption (such as regulatory requirements or funding structures) might be behind the differences between fintechs and banks. One exception is that banks that invest more on IT, like fintechs, provide more credit to lower income borrowers.

We finally analyze the implications of technology in banking for the transmission of monetary policy. Banks that invest more in IT reduce their lending by less in response to contractionary monetary policy shocks but also increase lending rates by more, consistent with them facing lower residual demand elasticity.

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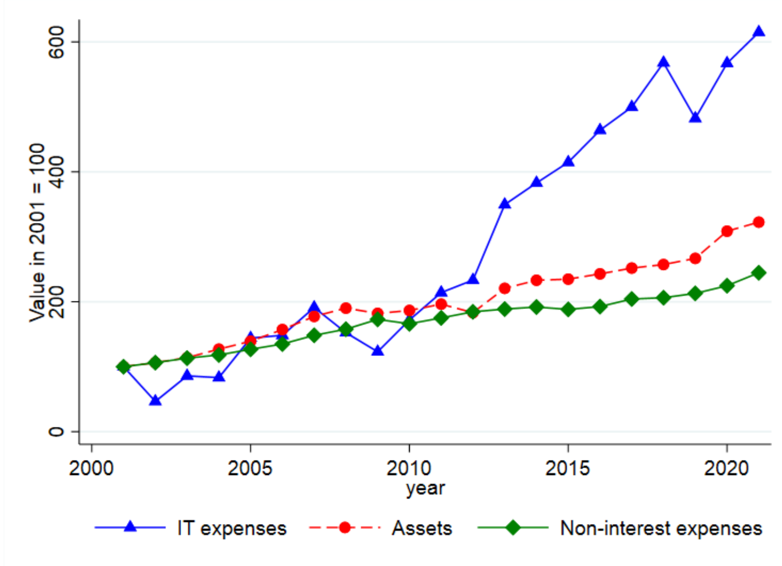
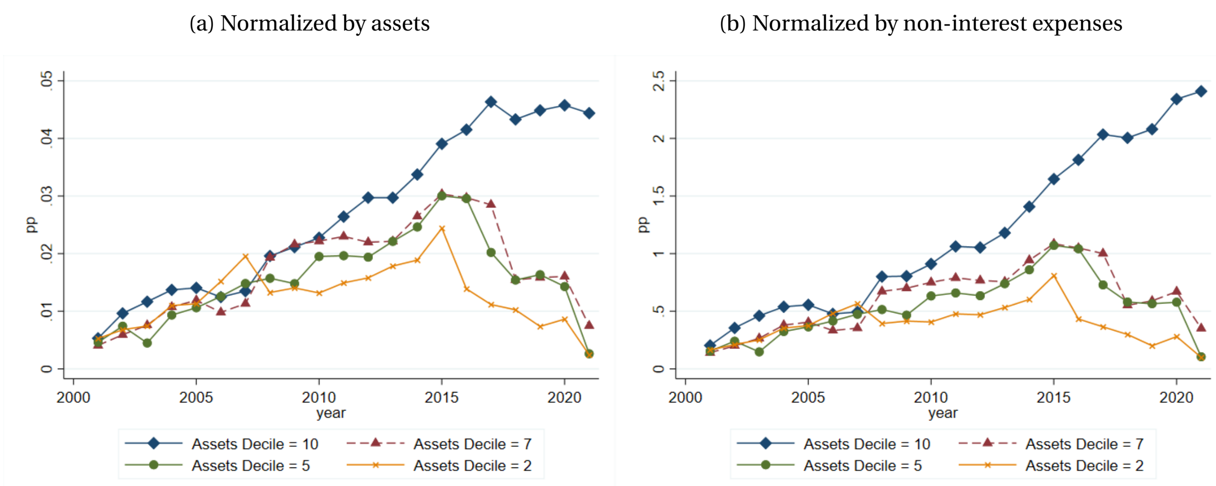
Figure 1: **Total Assets, non-interest expenses, IT expenses of US banks**



This Figure plots the total of assets, non-interest expenses, IT expenses of US Banks normalized by dividing by the 2001 value (so that 2001 = 100) from Call reports.

Figure 2: **IT expenses over time by bank size**



The Figure shows the average IT expenses over assets (Panel a) or over non-interest expenses (Panel b) for US banks according to bank size (decile of assets).

Figure 3: **Other non-interest expenses, deposits, loans, and capital over time by bank size**

(a) Other non-interest expenses

(b) Deposits

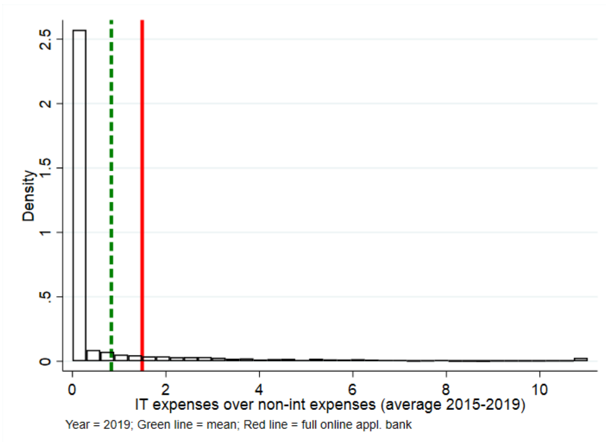
(c) Loans

(d) Equity

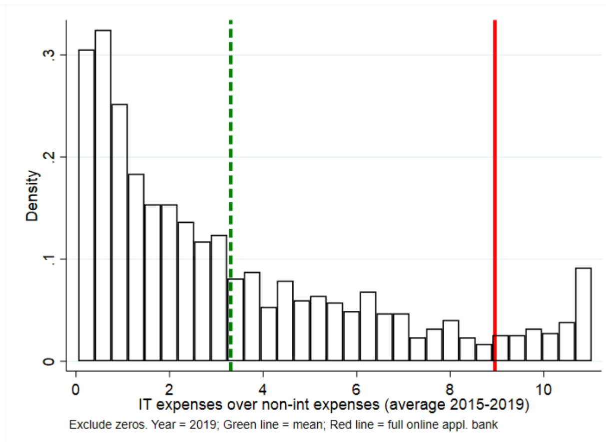
The figure shows the evolution of different balance sheet items over time, normalized by assets, by bank-size category.

Figure 4: **IT expenses normalized by non-interest income (2015-2019)**

(a) Unconditional



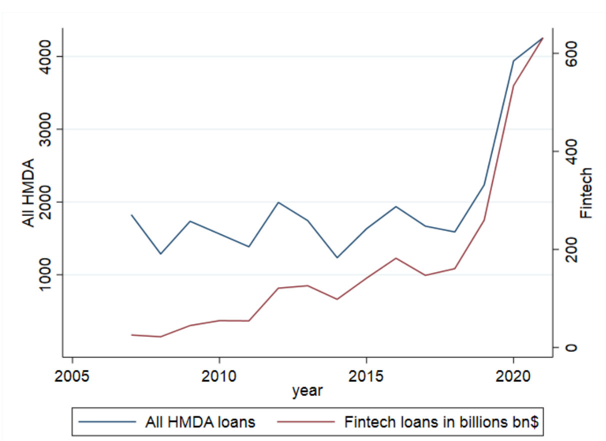
(b) Conditional on positive IT expenses



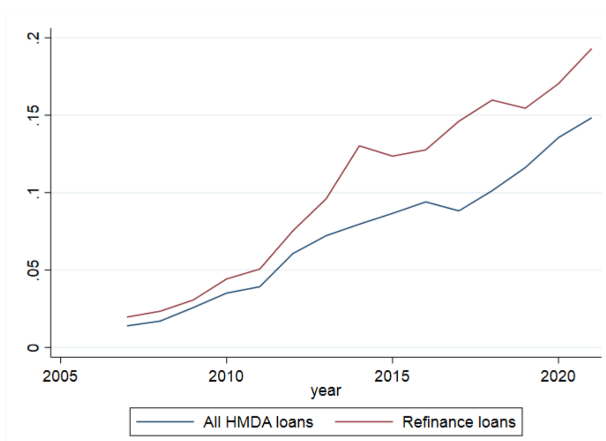
The figure shows the histogram of IT expenses over non-interest expenses, averaged during 2015-2019. The green dashed lines represent the averages, while the red lines represent the averages among banks that in 2019 offer the possibility of fully online mortgage application.

Figure 5: **Mortgage markets and fintech shares**

(a) Total mortgage value

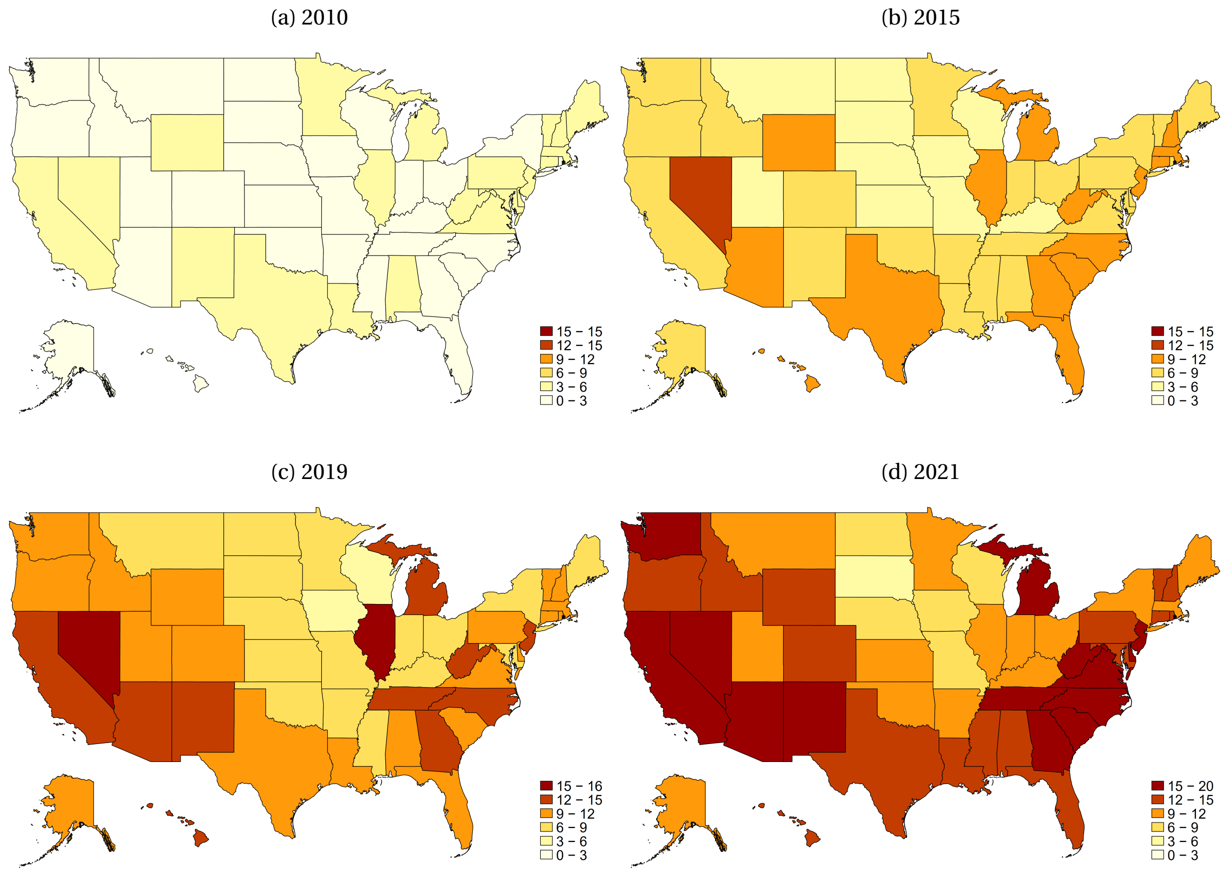


(b) Fintech share



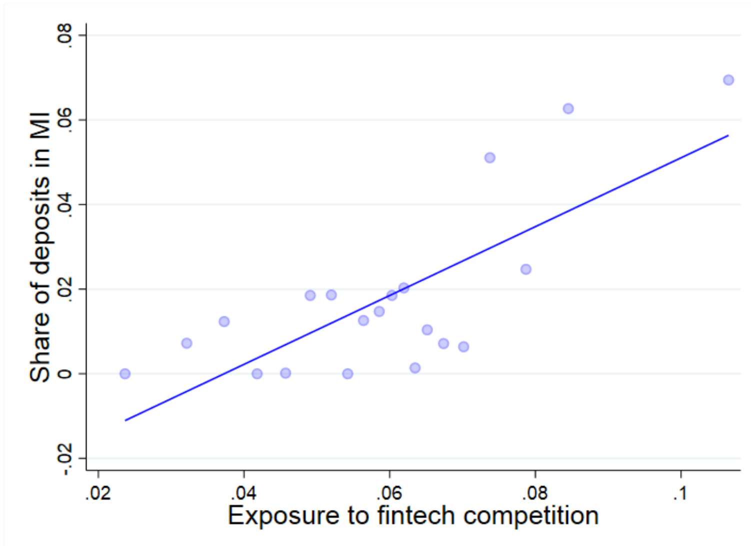
These figures focus on first lien, one-to-four family property type mortgage loans for purchase or refinance purposes in HMDA

Figure 6: **Fintech share in different states**



The Figure shows the fintech share of mortgage lending in different states for different years. These figures focus on first lien, one-to-four family property type mortgage loan market for purchase or refinance purposes in HMDA

Figure 7: **Share of deposits in Michigan and exposure to fintech competition**

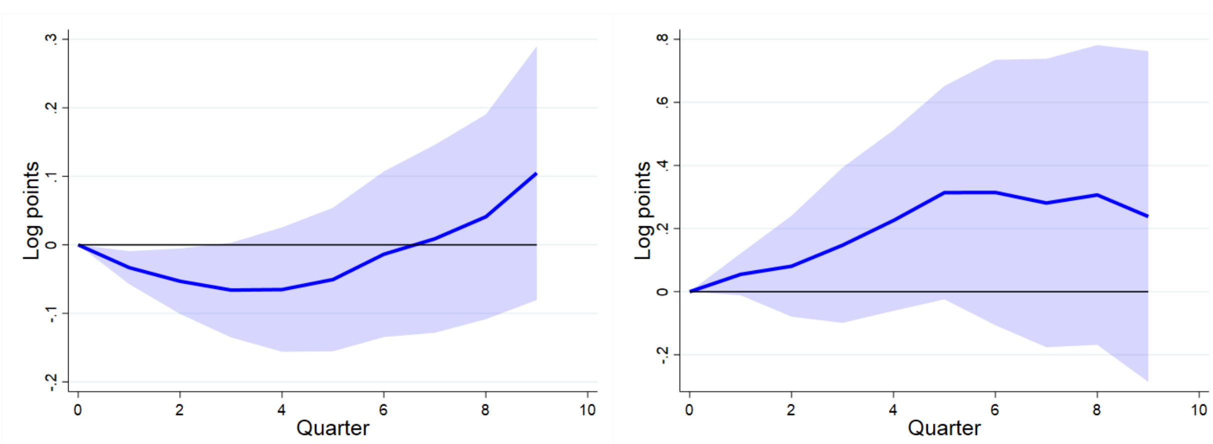


This figure plots a binscatter of the share of deposits in Michigan against a bank's exposure to fintech competition (average 2010-2015).

Figure 8: **Bank loans' response to a monetary policy shock**

(a) Loans

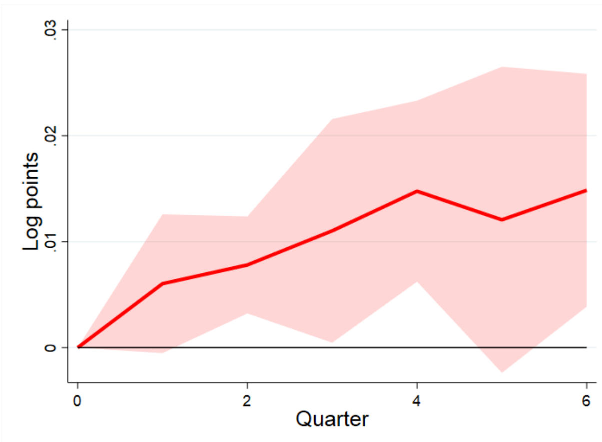
(b) Interest Earned on Loans



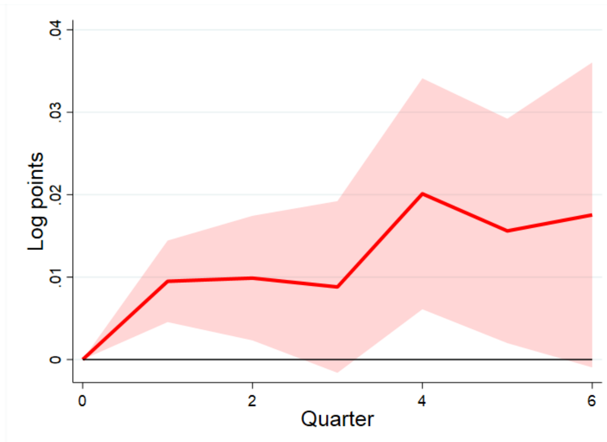
This Figure plots the cumulative impulse response function of a 100 basis points monetary policy shock (estimated by Jarociński and Karadi (2020)) to US banks' loans and interest rate earned on loans.

Figure 9: **Bank loans' response to monetary policy: IT heterogeneity**

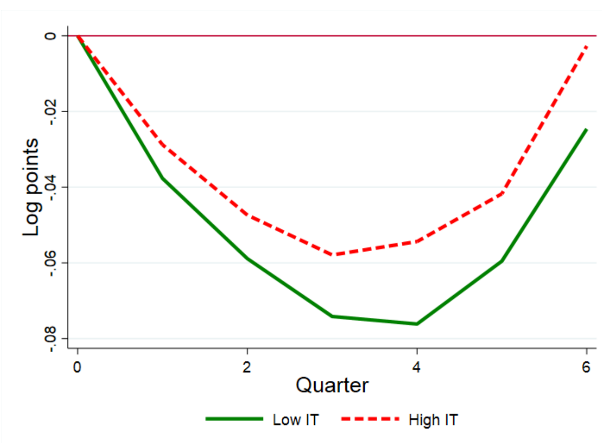
(a) Loans: Interaction term



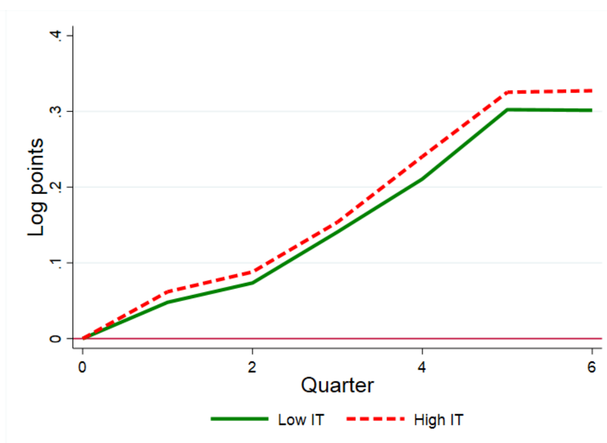
(b) Interest Rate Earned on Loans: Interaction term



(c) Loans: IRF of High vs low IT



(d) Interest Rate Earned on Loans: IRF of High vs low IT banks



Panels (a) and (b) plot the estimated coefficient of the interaction between a monetary policy shocks (estimated by Jarociński and Karadi (2020)) and a bank's IT expenditure over the last 5 years, normalized by non interest expenses. In panel (a) the dependent variable is log loans, while in panel (b) is the log interest earned on loans. Panels (b) and (c) plots the estimated cumulative impulse response function of a 100 basis points monetary policy shock (estimated by Jarociński and Karadi (2020)) to US banks' loans (panel c) or interest earned (panel d) for banks with high (0.5 sd above average) and low (0.5 sd below averge) IT expenditure.

Table 1: Determinants of banks' IT adoption

	IT Exp Over Assets (1)	IT Exp Over Interest Expense (2)
Log Assets	0.0144***	0.569***
	(4.70)	(4.85)
Fintech exposure	0.566*	19.38*
	(1.95)	(1.74)
Change in number of branches	-0.0208*	-0.715*
	(-1.78)	(-1.79)
STEM graduates	0.00239	0.504
	(0.05)	(0.32)
Math scores	0.000163	0.00511
	(1.22)	(1.08)
HHI of deposits	-0.00000397	-0.000176
	(-1.19)	(-1.43)
Share of adults with tertiary education	0.0875	3.649
	(1.05)	(1.21)
Income per capitax	-0.00157***	-0.0472**
	(-2.88)	(-2.33)
Population Density	-0.000000756	-0.0000326*
	(-1.52)	(-1.70)
Broadband	0.000187	0.000877
	(0.52)	(0.06)
Share Minority	0.000176	0.00497
	(0.96)	(0.71)
Loans / assets	-0.000248	-0.0100
	(-0.54)	(-0.60)
Net income / assets	-0.0159***	-0.564***
	(-2.65)	(-2.72)
Deposits / assets	0.00161***	0.0581***
	(3.45)	(3.40)
Non-interest share of income	0.000557***	0.0163***
	(5.36)	(4.03)
Equity / assets	-0.000990	-0.0391
	(-0.67)	(-0.70)
Sample	All banks; 2019	All banks; 2019
R2	0.161	0.154
Observations	2869	2869
Mean	.03	1.03
sd	0.07	2.3

Results of estimating the following equation:

$$IT_b = \alpha + \beta X_b + \epsilon_b$$

where b is a bank (BHC). IT_b are IT expenses normalized either by assets (1) or by non interest expenses (2), averaged across 2019-2015. X_b is a set of bank-level controls described in section 4. Observations are weighted by loans. T-statistics based on robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Determinants of banks' IT adoption

	IT expenses over Assets		IT expenses over non-interest expenses	
	(1)	(2)	(3)	(4)
Log Assets	0.0161***	0.0168***	0.634***	0.684***
	(3.91)	(3.51)	(4.09)	(3.76)
Small/medium × Fintech Exposure	0.342**	0.153	9.320*	3.383
	(2.06)	(1.02)	(1.88)	(0.70)
Large × Fintech Exposure	0.732*	1.262**	27.10*	47.07**
	(1.81)	(2.10)	(1.71)	(2.04)
Small/medium × change in number of branches	0.00979	0.00194	0.181	-0.00305
	(0.85)	(0.21)	(0.57)	(-0.01)
Large × change in number of branches	-0.0312**	-0.0367**	-1.009**	-1.206**
	(-2.19)	(-2.10)	(-2.06)	(-2.00)
Small/medium × STEM graduates	0.00162	0.0354**	-0.0509	1.181*
	(0.10)	(1.98)	(-0.09)	(1.91)
Large × STEM graduates	0.0144	0.0128	1.192	1.417
	(0.23)	(0.16)	(0.55)	(0.51)
Small/medium × HHI of deposits	0.00000268	0.00000156	0.000103	0.0000650
	(1.37)	(0.88)	(1.48)	(1.01)
Large × HHI of deposits	-0.00000541	-0.00000516	-0.000227	-0.000235
	(-1.28)	(-0.98)	(-1.47)	(-1.23)
Sample	Large = top 20%; 2019	Large = top 10%; 2019	Large = top 20%; 2019	Large = top 10%; 2019
R2	0.192	0.213	0.182	0.206
Observations	2869	2869	2869	2869
Mean	.03	.03	1.03	1.03
sd	0.07	0.07	2.3	2.3

Results of estimating the following equation:

$$IT_b = \alpha + \beta_L X_b \cdot Large_b + \beta_{SM} X_b \cdot (1 - Large_b) + \epsilon_b$$

where b is a bank (BHC). IT_b are IT expenses normalized either by assets (1-2) or by non interest expenses (3-4), averaged across 2019-2015. X_b is a set of bank-level covariates described in section 4. $Large_b$ is a dummy variable equal to one if the bank is in the the top 20% (1 and 2) or top 10% (2 and 4) of unconditional distribution of assets ($Large_b$ is also included in the controls). Observations are weighted by loans. T-statistics based on robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: IT adoption and fintech: IV estimation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Exposure to fintech	IT expenditure over assets				IT expenditure over non interest expenses			
Exposure to fintech		0.566*		5.474*	6.328*	19.38*		160.3*	196.3*
		(1.95)		(1.69)	(1.92)	(1.74)		(1.71)	(1.88)
Michigan share of deposits	0.0113***		0.0619**				1.813**		
	(3.63)		(2.28)				(2.08)		
log Assets	0.000344	0.0144***	0.0141***	0.0122***	0.00918**	0.569***	0.563***	0.508***	0.386***
	(0.98)	(4.70)	(4.74)	(3.65)	(2.48)	(4.85)	(4.89)	(4.40)	(3.03)
AR 10% CI:				[0.42, 12.89]	[0.74, 13.23]			[13.57, 369.56]	[18.95, 415.37]
Specification	First Stage	OLS	Reduced Form	IV	IV - no controls	OLS	Reduced Form	IV	IV - no controls
Full set of controls	✓	✓	✓	✓		✓	✓	✓	
Observations	2,848	2,869	2,848	2,848	2,848	2,869	2,848	2,848	2,848

Results of estimating the following two stage model:

$$ExposureFintech_b = \rho + \gamma Michigan_b + \lambda X_b + \eta_b$$

$$IT_b = \alpha + \beta ExposureFintech_b + \xi X_b + \epsilon_b$$

where b is a bank. IT_b are IT expenses normalized either by assets (2-5) or by non interest expenses (6-9), averaged across 2019-2015. X_b is a set of bank-level controls described in section 4. $ExposureFintech_b$ is a measure of bank-level exposure to early (i.e. 2010-2015) exposure to fintech competition in the mortgage market. The instrument $Michigan_b$ is the share of deposits in the state of Michigan over the same years. Coumn (1) presents the first stage, columns (2) and (6) reproduce OLS estimates, columns (3) and (7) present the reduced form regressions of instrument on outcome of interest, while columns (4), (5), (8), and (9) present the 2SLS estimates with and without the full set of controls. T-statistics based on robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The row "AR 10% CI" present 10% confidence intervals which are consistent under the presence of a weak instrument problem.

Table 4: Originator type and Lending Behavior

	LTV	DTI	Loan Amt	Property	Interest Rate	Term	Income	Low Income	Minority	Refinance
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
High IT	0.02	0.39**	-0.02	-0.01	0.03	0.20	-0.03***	0.02***	-0.01***	0.01
	(0.42)	(0.17)	(0.01)	(0.01)	(0.05)	(1.91)	(0.01)	(0.00)	(0.00)	(0.01)
Fintech	2.99***	1.22***	-0.04*	-0.10***	0.09	2.19	-0.09***	0.01**	0.01*	0.14***
	(0.64)	(0.21)	(0.02)	(0.02)	(0.11)	(2.73)	(0.01)	(0.01)	(0.01)	(0.03)
Non Banks	3.24***	1.30***	-0.01	-0.06***	0.04	9.40***	-0.11***	0.02***	0.01***	-0.02
	(0.35)	(0.12)	(0.01)	(0.01)	(0.05)	(1.81)	(0.01)	(0.00)	(0.00)	(0.02)
Observations	31,047,050	30,565,776	33,621,734	31,874,086	32,897,144	32,924,054	30,874,863	30,874,863	29,262,106	33,621,734
R^2	0.441	0.124	0.372	0.499	0.373	0.046	0.199	0.094	0.159	0.142
Loan controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
County-Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Mean Low IT	72.5	32.5	5.48	12.8	3.51	319	4.65	.198	.248	.540
SD Low IT	19.8	11.4	.712	.739	.838	96.4	.715	.399	.432	.498
High IT = Fintech	.00***	.00***	.20	.00***	.60	.36	.00***	.72	.00***	.00***
Non Bank = Fintech	.65	.70	.06**	.07**	.63	.00***	.34	.40	.94	.00***

Notes: results from estimating $Y_{ilzt} = \beta \text{Class}_{lt} + \gamma X^1_{izt} + \zeta X^2_{lt-1} + \delta_{zt} + \epsilon_{ilzt}$ where Y_{ilzt} is the dependent variable for loan i given by lender l in county z at year t, Class_{lt} is the class of lender: low IT bank (base), high IT bank, fintech or non bank, X^1_{izt} are the loan level controls, X^2_{lt-1} are lender controls which include the log amount of mortgages issued by lender l in the previous year to proxy for the size of the lender, and δ_{zt} are county-year fixed effects. The loan level controls include product type, purchaser type loan purpose, occupancy type and hoepa status. All standard errors are clustered at the lender level. Combined loan to value ratio, monthly debt to monthly income ratio, log of loan amount, log of property value, interest rate, loan term (in months), log of income of the borrower, a dummy for whether the income of borrower is in the bottom 20% percentile, a dummy for borrower is non-white or hispanic and a dummy for whether the loan purpose is for refinancing, correspond to columns 1-10. The last four rows correspond to the mean value of the dependent variable for the base Low IT banks, the standard deviation for the same, the p value for the test that the coefficient for the high IT bank and fintech are equal and the p value for the test that the coefficient for the fintech and non banks are equal respectively.

Table 5: Log income + Minority (application level)

	Income			Minority		
	(1)	(2)	(3)	(4)	(5)	(6)
High IT	0.00	-0.00	-0.02***	0.01	0.01	-0.00
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
Fintech	-0.15***	-0.04*	-0.06***	0.09***	0.05***	0.02***
	(0.05)	(0.03)	(0.01)	(0.02)	(0.02)	(0.01)
Non Banks	-0.14***	-0.04***	-0.08***	0.09***	0.06***	0.02***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
Observations	45,380,485	32,811,759	32,811,759	41,997,843	30,373,622	30,373,622
R^2	0.009	0.101	0.198	0.009	0.032	0.156
Loan and Lender controls	no	yes	yes	no	yes	yes
County-Year FE	no	no	yes	no	no	yes

Notes: results from estimating $Y_{ilzt} = \beta \text{Class}_{lt} + \gamma X^1_{izt} + \zeta X^2_{lt-1} + \delta_{zt} + \epsilon_{ilzt}$ where Y_{ilzt} is the log of income of applicant of loan i to lender l in county z at year t in Columns (1)-(3) and a dummy for whether the applicant of loan i is non-white or hispanic in Columns (4)-(6), Class_{lt} is the class of lender : low IT bank (base), high IT bank, fintech or non bank, X^1_{izt} are the loan level controls, X^2_{lt-1} are lender controls which include the log amount of mortgages issued by lender l in the previous year to proxy for the size of the lender, and δ_{zt} are county-year fixed effects. The loan level controls include product type, purchaser type loan purpose, occupancy type and hoepa status. All standard errors are clustered at the lender level.

Table 6: Acceptance rate of different lenders

	(1)	(2)	(3)
High IT	-0.06	-0.06	0.17
	(0.04)	(0.05)	(0.11)
Fintech	0.04	0.23^{***}	0.39^{***}
	(0.06)	(0.06)	(0.12)
Non Banks	0.01	0.08	0.32^{***}
	(0.04)	(0.06)	(0.11)
Minority=1 × Low IT			0.01
			(0.01)
Minority=1 × High IT			-0.01
			(0.01)
Minority=1 × Fintech			0.01^{***}
			(0.00)
Minority=1 × Non Banks			0.01^{***}
			(0.00)
Income × Low IT			0.03^{***}
			(0.01)
Income × High IT			-0.03^{*}
			(0.01)
Income × Fintech			-0.03^{**}
			(0.01)
Income × Non Banks			-0.03^{**}
			(0.01)
Observations	54,686,838	39,568,999	28,064,101
R^2	0.003	0.128	0.182
Loan-Lender Controls	No	Yes	Yes
County × Year FE	No	Yes	Yes

Notes: results from estimating $\text{Accept}_{ilzt} = \beta \text{Class}_{lt} + \text{Class}_{lt} \cdot \text{minority}_{ilzt} + \text{Class}_{lt} \cdot \text{income}_{ilzt} + \gamma X^1_{izt} + \zeta X^2_{lt-1} + \delta_{zt} + \epsilon_{ilzt}$ where $Accept_{ilzt}$ is a dummy for whether the loan application i was accepted, Class_{lt} is the class of lender : low IT bank (base), high IT bank, fintech or non bank, minority is a dummy for whether at least one of the applicants is non-white or hispanic,income is the log of income of the borrower, X^1_{izt} are the loan level controls, X^2_{lt-1} are lender controls which include the log amount of mortgages issued by lender l in the previous year to proxy for the size of the lender, and δ_{zt} are county-year fixed effects. The loan level controls include product type, purchaser type loan purpose, occupancy type and hoepa status. All standard errors are clustered at the lender level.

Table 7: Monetary policy, IT, and syndicated lending

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Log new credit				
MP shock t-1 × IT over non interest exp	0.126**	0.0451**	0.0364*				0.0378**	
	(2.41)	(2.19)	(1.92)				(2.01)	
MP shock t-2 × IT over non interest exp	0.0775	0.0395**	0.0221				0.0126	
	(1.20)	(2.02)	(1.06)				(0.83)	
MP shock t-3 × IT over non interest exp	-0.0329	0.00845	-0.0138				-0.0172	
	(-0.65)	(0.55)	(-0.81)				(-1.02)	
MP shock t-1 × IT over assets				4.336***	1.523**	1.297*		1.358**
				(2.66)	(2.13)	(1.98)		(2.08)
MP shock t-2 × IT over assets				2.854	1.326*	0.736		0.478
				(1.35)	(1.92)	(1.02)		(0.90)
MP shock t-3 × IT over assets				-0.873	0.354	-0.359		-0.436
				(-0.53)	(0.66)	(-0.62)		(-0.78)
Interacted controls							✓	✓
FEs (Bank FEs always included)	Borrower	Borrower + Quarter	Quarter*Borrower	Borrower	Borrower + Quarter	Quarter*Borrower	Quarter*Borrower	Quarter*Borrower
R2	0.608	0.640	0.798	0.608	0.640	0.798	0.798	0.798
Observations	105,213	105,213	105,213	105,213	105,213	105,213	105,213	105,213

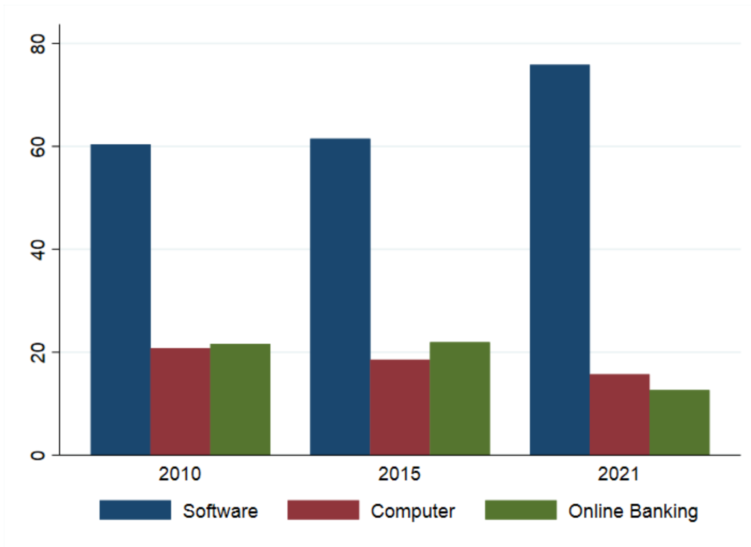
Results of estimating the following linear regression:

$$\log credit_{f,b,t} = \delta_{f,t} + \zeta_b + \sum^{h=1,2,3} \left(\alpha^h MP_{t-h} \cdot IT_{b,y(t-4)}\right) + \gamma X b, t + \epsilon_{b,t}$$

where b is a bank, f is a borrowing firm, and t a quarter. $\log credit_{f,b,t}$ is the log amount of credit provided from b to f through new syndicated loans in quarter t, MP_{t-h} is the monetary policy shock by Jarociński and Karadi (2020) aggregated at the quarterly level, and $IT_{b,y(t-4)}$ are b's IT expenses over the previous 5 years, normalized either by assets or by non interest expenses. The coefficients α^h, together with t-stat based on standard errors double clustered at the bank and quarter level are reported. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

8 Appendix Tables and Figures

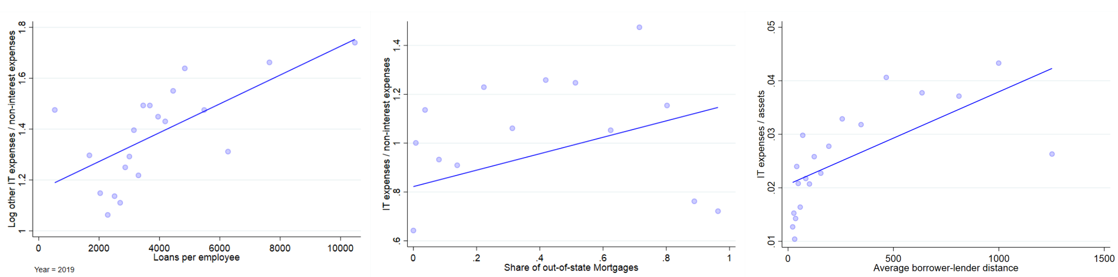
Figure A1: **Commonly used IT words**



This figure plots the share of banks with non-zero IT expenses which mention at least once in the year one of three keywords: software, computer(s), online banking (electronic banking).

Figure A2: **IT expenses, loans per employee, and borrower-lender distance**

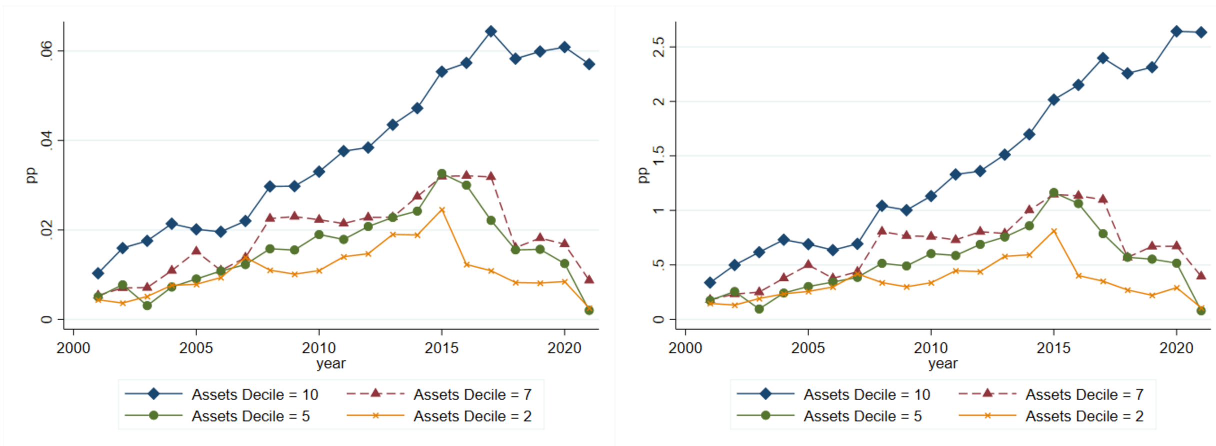
(a) Loans per employees (b) Out-of-state mortgages (c) Lending distance



The figure shows binscatter plots of IT over assets against loans per employee (Panel a), share of HMDA mortgages in states where the bank has no branches (Panel b), and the average distance between the bank's headquarter and the borrower property weighted by size of the mortgages.

Figure A3: **IT expenses over time by bank size–balanced panel**

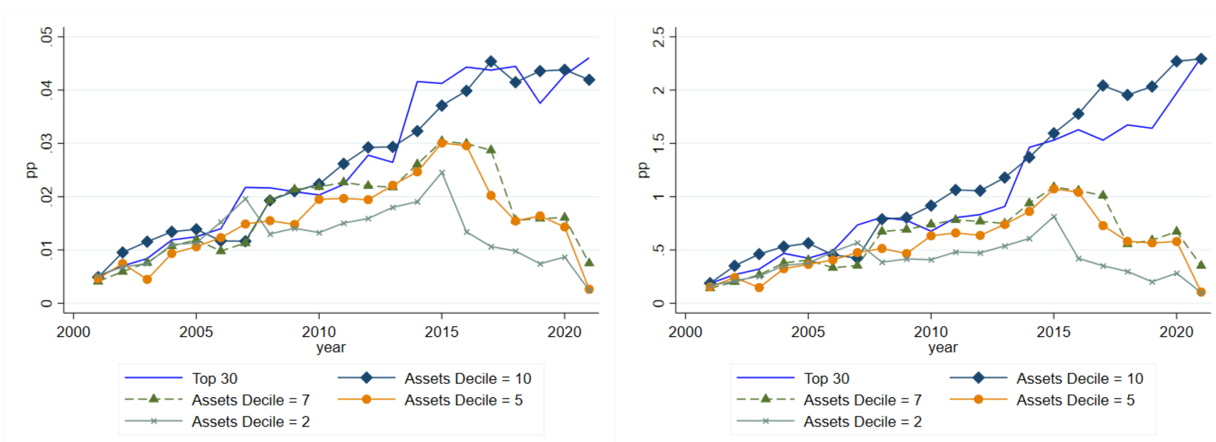
(a) Normalized by assets (b) Normalized by non-interest expenses



The Figure shows the average IT expenses over assets (Panel a) or over non-interest expenses (Panel b) for US banks according to bank size (decile of assets). Only banks that are present in the sample for all the years are included.

Figure A4: **IT expenses over time by bank size–isolating top 30**

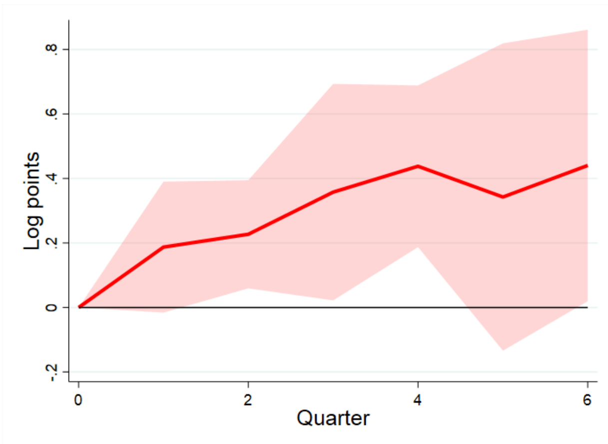
(a) Normalized by assets (b) Normalized by non-interest expenses



The Figure shows the average IT expenses over assets (Panel a) or over non-interest expenses (Panel b) for US banks according to bank size. Bank size is measured by decile of assets, except for all banks that belong to the largest 30 bank holding companies, which are included in a separate group.

Figure A5: **Bank loans' response to monetary policy: IT heterogeneity with IT normalized by assets**

(a) Loans: Interaction term



(b) Interest Rate Earned on Loans Interaction term

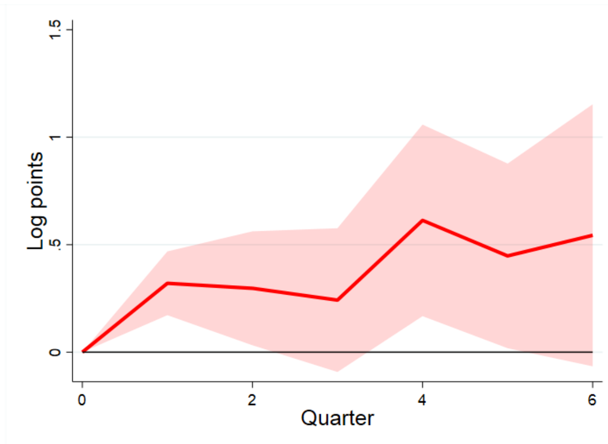
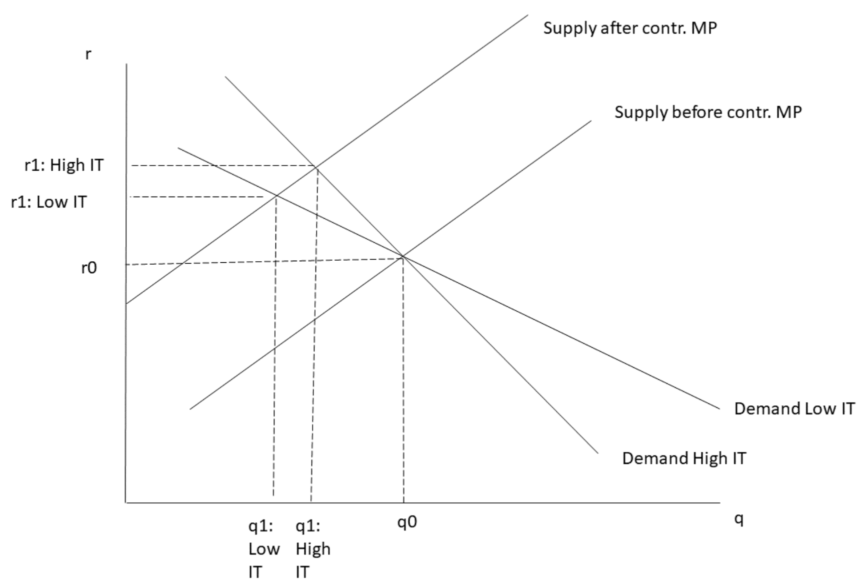


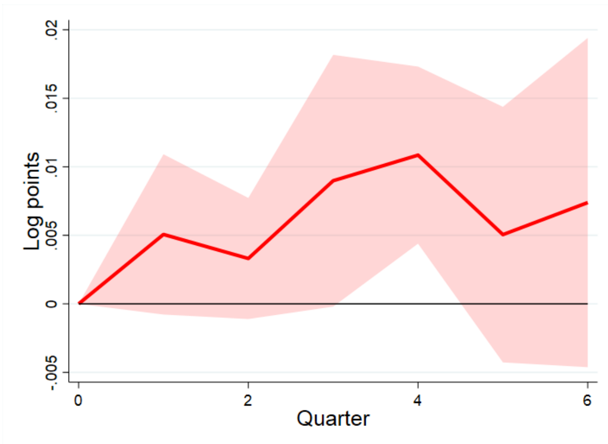
Figure A6: **Graphical Illustration of the impact of MP tightening**



This figure graphically illustrates the impact of an monetary tightening–translating into a negative supply shock–on banks which face low vs high elasticity of residual demand (high vs low IT banks).

Figure A7: **Bank loans' response to monetary policy: IT heterogeneity with additional interacted controls**

(a) Loans: Interaction term



(b) Interest Rate Earned on Loans Interaction term

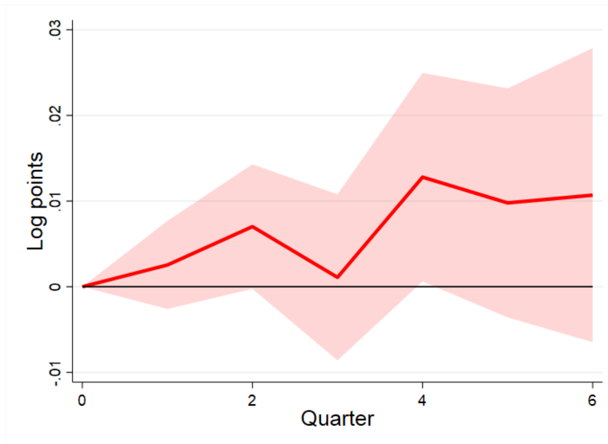


Table A1: Summary statistics of the independent variables in ??

	(1)				
	Mean	N	Sd	Min	Max
Log assets	13.06	2872	1.40	9.88	17.93
Fintech exposusre	0.06	2872	0.02	0.01	0.18
Branch growth	0.12	2872	0.31	-1.69	1.94
STEM graduates	0.38	2872	0.13	0.04	1.00
Math score	617.62	2872	47.33	445.53	780.00
HHI of deposits	1983.19	2872	1089.98	548.54	9684.28
Education	0.27	2872	0.07	0.10	0.48
Income per capita	25.31	2872	8.81	6.92	89.59
Population density	1355.74	2872	5103.47	1.33	69357.68
Broadband	27.61	2872	16.70	0.00	70.00
Share minority	14.72	2872	19.19	0.00	85.65
Loans/Assets	64.24	2872	14.95	0.00	88.57
Net income/Assets	0.83	2872	0.68	-1.90	6.50
Deposits/Assets	13.74	2872	9.09	0.00	39.14
Share of non interest income	64.47	2872	34.28	0.00	100.00
Equity/Assets	11.25	2872	3.48	2.00	39.60

Table A2: Bank loans' response to monetary policy: IT heterogeneity

	(1)	(2)	(3)	(4)	(5)
	Delta log loans				
α^h	0.00604	0.00781***	0.0110*	0.0148***	0.0121
	(1.52)	(2.81)	(1.72)	(2.84)	(1.37)
Horizon (h)	1	2	3	4	5
R2	0.0418	0.0894	0.124	0.169	0.194
Observations	494,680	489,609	484,540	479,554	474,595

Heterogeneity by IT adoption of the Cumulative Impulse Response Function (Jordà, 2005) of loans to monetary policy shocks: $\Delta^h loans_{b,t} = \delta_b + \zeta_t + \alpha^h MP_{t-1} \cdot IT_{b,y(t-4)} + \gamma Xb, t + \epsilon_{b,t}$ where $\log loans_{b,t}$ is the (log) amount of net loans on bank's b balance sheet on quarter t, $\Delta^h \log loans_{b,t} = \log loans_{b,t+h} - \log loans_{b,t-1}$, δ_b are bank fixed effects, ζ_t are quarter fixed effects, MP_{t-1} is the monetary policy shock (estimated by Jarociński and Karadi (2020)) in the quarter $t-1$, and Xb, t is a set of controls. The coefficients α^h, together with t-stat based on standard errors double clustered at the bank and quarter level are reported. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Interest earned on loans' response to monetary policy: IT heterogeneity

	(1)	(2)	(3)	(4)	(5)
	Delta log interest earned on loans				
α^h	0.00949***	0.00988**	0.00880	0.0201**	0.0156*
	(3.16)	(2.15)	(1.39)	(2.36)	(1.89)
Horizon (h)	1	2	3	4	5
R2	0.0317	0.0833	0.127	0.209	0.253
Observations	491,021	486,056	481,075	476,176	471,281

Heterogeneity by IT adoption of the Cumulative Impulse Response Function (Jordà, 2005) of loans to monetary policy shocks: $\Delta^h \log r_{b,t} = \delta_b + \zeta_t + \alpha^h MP_{t-1} \cdot IT_{b,y(t-4)} + \gamma Xb, t + \epsilon_{b,t}$ where $\log r_{b,t}$ is the (log) interest earned on loans (measured as interest income on loans over loans) on bank's b balance sheet on quarter t, $\Delta^h \log loans_{b,t} = \log loans_{b,t+h} - \log loans_{b,t-1}$, δ_b are bank fixed effects, ζ_t are quarter fixed effects, MP_{t-1} is the monetary policy shock (estimated by Jarociński and Karadi (2020)) in the quarter $t-1$, and Xb, t is a set of controls. The coefficients α^h, together with t-stat based on standard errors double clustered at the bank and quarter level are reported. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Combined Loan to Value Ratio

	(1)	(2)	(3)	(4)
High IT	-1.10	-0.07	0.02	0.04
	(1.05)	(0.44)	(0.42)	(0.42)
Fintech	0.00	3.04***	2.99***	3.23***
	(1.70)	(0.63)	(0.64)	(0.64)
Non Banks	6.37***	2.69***	3.24***	3.12***
	(0.89)	(0.34)	(0.35)	(0.34)
Observations	34136544	31047051	31047050	29564305
R^2	0.031	0.416	0.441	0.446
Loan and lender controls	no	yes	yes	yes
County-Year FE	no	no	yes	yes
Borrower controls	no	no	no	yes

Notes: results from estimating $Y_{ilzt} = \beta \text{Class}_{lt} + \gamma X^1_{izt} + \zeta X^2_{lt-1} + \delta_{zt} + \epsilon_{ilzt}$ where Y_{ilzt} is the combined loan to value ratio for loan i given by lender l in county z at year t, Class_{lt} is the class of lender : low IT bank (base), high IT bank, fintech or non bank, X^1_{izt} are the loan and borrower level controls, X^2_{lt-1} are lender controls which include the log amount of mortgages issued by lender l in the previous year to proxy for the size of the lender, and δ_{zt} are county-year fixed effects. The loan level controls include product type, purchaser type loan purpose, occupancy type and hoepa status, and the borrower level controls include log of income of the borrower. All standard errors are clustered at the lender level.

Table A5: Log Loan Amount

	(1)	(2)	(3)	(4)
High IT	0.02	0.01	-0.02	-0.00
	(0.03)	(0.02)	(0.01)	(0.01)
Fintech	0.05	-0.03	-0.04*	0.01
	(0.04)	(0.04)	(0.02)	(0.02)
Non Banks	0.08***	0.09***	-0.01	0.05***
	(0.03)	(0.02)	(0.01)	(0.01)
Observations	37292402	33621734	33621734	30874863
R^2	0.003	0.082	0.372	0.619
Loan and lender controls	no	yes	yes	yes
County-Year FE	no	no	yes	yes
Borrower controls	no	no	no	yes

Notes: results from estimating $Y_{ilzt} = \beta \text{Class}_{lt} + \gamma X^1_{izt} + \zeta X^2_{lt-1} + \delta_{zt} + \epsilon_{ilzt}$ where Y_{ilzt} is the log of loan amount (in thousands of dollars) for loan i given by lender l in county z at year t, Class_{lt} is the class of lender : low IT bank (base), high IT bank, fintech or non bank, X^1_{izt} are the loan and borrower level controls, X^2_{lt-1} are lender controls which include the log amount of mortgages issued by lender l in the previous year to proxy for the size of the lender, and δ_{zt} are county-year fixed effects. The loan level controls include product type, purchaser type loan purpose, occupancy type and hoepa status, and the borrower level controls include log of income of the borrower. All standard errors are clustered at the lender level.

Table A6: Log Property Value

	(1)	(2)	(3)	(4)
High IT	0.03	0.01	-0.01	0.00
	(0.04)	(0.02)	(0.01)	(0.01)
Fintech	-0.01	-0.09**	-0.10***	-0.05***
	(0.05)	(0.04)	(0.02)	(0.02)
Non Banks	-0.05	0.05***	-0.06***	-0.00
	(0.04)	(0.02)	(0.01)	(0.01)
Observations	35163628	31874086	31874086	30008267
R^2	0.002	0.171	0.499	0.690
Loan and lender controls	no	yes	yes	yes
County-Year FE	no	no	yes	yes
Borrower controls	no	no	no	yes

Notes: results from estimating $Y_{ilzt} = \beta \text{Class}_{lt} + \gamma X^1_{izt} + \zeta X^2_{lt-1} + \delta_{zt} + \epsilon_{ilzt}$ where Y_{ilzt} is the log of preoperty value for loan i given by lender l in county z at year t, Class_{lt} is the class of lender : low IT bank (base), high IT bank, fintech or non bank, X^1_{izt} are the loan and borrower level controls, X^2_{lt-1} are lender controls which include the log amount of mortgages issued by lender l in the previous year to proxy for the size of the lender, and δ_{zt} are county-year fixed effects. The loan level controls include product type, purchaser type loan purpose, occupancy type and hoepa status, and the borrower level controls include log of income of the borrower. All standard errors are clustered at the lender level.

Table A7: Interest Rate

	(1)	(2)	(3)	(4)
High IT	-0.02	0.02	0.03	0.03
	(0.10)	(0.08)	(0.05)	(0.05)
Fintech	-0.21	0.12	0.09	0.08
	(0.19)	(0.16)	(0.11)	(0.11)
Non Banks	-0.05	-0.01	0.04	0.03
	(0.08)	(0.07)	(0.05)	(0.05)
Observations	36297090	32897144	32897144	30182617
R^2	0.006	0.173	0.373	0.369
Loan and lender controls	no	yes	yes	yes
County-Year FE	no	no	yes	yes
Borrower controls	no	no	no	yes

Notes: results from estimating $Y_{ilzt} = \beta \text{Class}_{lt} + \gamma X^1_{izt} + \zeta X^2_{lt-1} + \delta_{zt} + \epsilon_{ilzt}$ where Y_{ilzt} is the interest rate for loan i given by lender l in county z at year t, Class_{lt} is the class of lender : low IT bank (base), high IT bank, fintech or non bank, X^1_{izt} are the loan and borrower level controls, X^2_{lt-1} are lender controls which include the log amount of mortgages issued by lender l in the previous year to proxy for the size of the lender, and δ_{zt} are county-year fixed effects. The loan level controls include product type, purchaser type loan purpose, occupancy type and hoepa status, and the borrower level controls include log of income of the borrower. All standard errors are clustered at the lender level.

Table A8: Loan Term

	(1)	(2)	(3)	(4)
High IT	0.15	0.76	0.20	0.18
	(2.48)	(2.02)	(1.91)	(1.87)
Fintech	5.27	2.79	2.19	1.36
	(4.23)	(2.96)	(2.73)	(2.89)
Non Banks	23.19***	12.90***	9.40***	7.97***
	(2.09)	(1.86)	(1.81)	(1.81)
Observations	36168164	32924054	32924054	30206656
R^2	0.005	0.039	0.046	0.067
Loan and lender controls	no	yes	yes	yes
County-Year FE	no	no	yes	yes
Borrower controls	no	no	no	yes

Notes: results from estimating $Y_{ilzt} = \beta \text{Class}_{lt} + \gamma X^1_{izt} + \zeta X^2_{lt-1} + \delta_{zt} + \epsilon_{ilzt}$ where Y_{ilzt} is the loan term (in months) for loan i given by lender l in county z at year t, Class_{lt} is the class of lender : low IT bank (base), high IT bank, fintech or non bank, X^1_{izt} are the loan and borrower level controls, X^2_{lt-1} are lender controls which include the log amount of mortgages issued by lender l in the previous year to proxy for the size of the lender, and δ_{zt} are county-year fixed effects. The loan level controls include product type, purchaser type loan purpose, occupancy type and hoepa status, and the borrower level controls include log of income of the borrower. All standard errors are clustered at the lender level.

Table A9: Log income of borrowers

	(1)	(2)	(3)
High IT	-0.02	-0.02	-0.03***
	(0.03)	(0.02)	(0.01)
Fintech	-0.13***	-0.10***	-0.09***
	(0.03)	(0.03)	(0.01)
Non Banks	-0.17***	-0.06***	-0.11***
	(0.02)	(0.01)	(0.01)
Observations	33879919	30874863	30874863
R^2	0.012	0.103	0.199
Loan and lender controls	no	yes	yes
County-Year FE	no	no	yes

Notes: results from estimating $Y_{ilzt} = \beta \text{Class}_{lt} + \gamma X^1_{izt} + \zeta X^2_{lt-1} + \delta_{zt} + \epsilon_{ilzt}$ where Y_{ilzt} is the log of income (in thousands of dollars) of borrowers for loan i given by lender l in county z at year t, Class_{lt} is the class of lender : low IT bank (base), high IT bank, fintech or non bank, X^1_{izt} are the loan level controls, X^2_{lt-1} are lender controls which include the log amount of mortgages issued by lender l in the previous year to proxy for the size of the lender, and δ_{zt} are county-year fixed effects. The loan level controls include product type, purchaser type loan purpose, occupancy type and hoepa status. All standard errors are clustered at the lender level.

Table A10: Low Income (bottom quintile) Borrowers

	(1)	(2)	(3)
High IT	0.01	0.01*	0.02***
	(0.01)	(0.01)	(0.00)
Fintech	0.01	0.01	0.01**
	(0.01)	(0.01)	(0.01)
Non Banks	0.02***	-0.00	0.02***
	(0.01)	(0.01)	(0.00)
Observations	33879919	30874863	30874863
R^2	0.001	0.039	0.094
Loan and lender controls	no	yes	yes
County-Year FE	no	no	yes

Notes: results from estimating $Y_{ilzt} = \beta \text{Class}_{lt} + \gamma X^1_{izt} + \zeta X^2_{lt-1} + \delta_{zt} + \epsilon_{ilzt}$ where Y_{ilzt} is a dummy for the poorest income quintile for loan i given by lender l in county z at year t, Class_{lt} is the class of lender : low IT bank (base), high IT bank, fintech or non bank, X^1_{izt} are the loan level controls, X^2_{lt-1} are lender controls which include the log amount of mortgages issued by lender l in the previous year to proxy for the size of the lender, and δ_{zt} are county-year fixed effects. The loan level controls include product type, purchaser type loan purpose, occupancy type and hoepa status. All standard errors are clustered at the lender level.

Table A11: Debt to income ratio

	(1)	(2)	(3)
High IT	0.43	0.49^{**}	0.39^{**}
	(0.29)	(0.20)	(0.17)
Fintech	2.28^{***}	1.41^{***}	1.22^{***}
	(0.46)	(0.27)	(0.21)
Non Banks	3.24^{***}	1.71^{***}	1.30^{***}
	(0.22)	(0.15)	(0.12)
Observations	33255660	30565776	30565776
R^2	0.014	0.104	0.124
Loan and lender controls	no	yes	yes
County-Year FE	no	no	yes

Notes: results from estimating $Y_{ilzt} = \beta \text{Class}_{lt} + \gamma X^1_{izt} + \zeta X^2_{lt-1} + \delta_{zt} + \epsilon_{ilzt}$ where Y_{ilzt} is the monthly debt to monthly income ratio for loan i given by lender l in county z at year t, Class_{lt} is the class of lender : low IT bank (base), high IT bank, fintech or non bank, X^1_{izt} are the loan level controls, X^2_{lt-1} are lender controls which include the log amount of mortgages issued by lender l in the previous year to proxy for the size of the lender, and δ_{zt} are county-year fixed effects. The loan level controls include product type, purchaser type loan purpose, occupancy type and hoepa status. All standard errors are clustered at the lender level.

Table A12: Minority

	(1)	(2)	(3)	(4)
High IT	0.01	0.00	-0.01***	-0.01***
	(0.01)	(0.01)	(0.00)	(0.00)
Fintech	0.10***	0.03**	0.01*	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Non Banks	0.11***	0.06***	0.01***	0.01**
	(0.01)	(0.01)	(0.00)	(0.00)
Observations	32108468	29262106	29262106	26975760
R^2	0.010	0.036	0.159	0.164
Loan and lender controls	no	yes	yes	yes
County-Year FE	no	no	yes	yes
Borrower controls	no	no	no	yes

Notes: results from estimating $Y_{ilzt} = \beta \text{Class}_{lt} + \gamma X^1_{izt} + \zeta X^2_{lt-1} + \delta_{zt} + \epsilon_{ilzt}$ where Y_{ilzt} is a dummy for whether at least one of the applicants is non-white or hispanic for loan i given by lender l in county z at year t, Class_{lt} is the class of lender : low IT bank (base), high IT bank, fintech or non bank, X^1_{izt} are the loan and borrower level controls, X^2_{lt-1} are lender controls which include the log amount of mortgages issued by lender l in the previous year to proxy for the size of the lender, and δ_{zt} are county-year fixed effects. The loan level controls include product type, purchaser type loan purpose, occupancy type and hoepa status, and the borrower level controls include log of income of the borrower. All standard errors are clustered at the lender level.

Table A13: Bank IT Investments and Lending Behavior

	LTV	DTI	Loan Amt	Property	Interest Rate	Term	Income	Low Income	Minority
IT expenses	0.33	0.88***	-0.02	-0.01	-0.13	-5.67*	-0.05**	0.03***	-0.02***
	(0.46)	(0.21)	(0.02)	(0.02)	(0.10)	(3.27)	(0.02)	(0.01)	(0.01)
Observations	9620199	9495860	10386926	9654250	9707882	9716887	9927870	9927870	9423586
R^2	0.386	0.081	0.382	0.490	0.346	0.131	0.221	0.089	0.155
Loan-Lender controls	yes	yes	yes	yes	yes	yes	yes	yes	yes
County-Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes

Notes: results from estimating only for banks $Y_{ilzt} = \beta * \text{Avg IT}_{lt-1} + \gamma X^1_{izt} + \zeta X^2_{lt-1} + \delta_{zt} + \epsilon_{ilzt}$ where Y_{ilzt} is the dependent variables, X^2_{lt-1} are lender controls which include log assets, deposits/assets, equity/assets, loans/assets and share of non-interest income, and δ_{zt} are county-year fixed effects. The loan level controls include product type, purchaser type loan purpose, occupancy type and hoepa status, and the borrower level controls include log of income of the borrower. All standard errors are clustered at the lender level. errors are clustered at the lender level. Combined loan to value ratio, monthly debt to monthly income ratio, log of loan amount, log of property value, interest rate, loan term (in months), log of income of the borrower, a dummy for whether the income of borrower is in the bottom 20% percentile, and a dummy for whether at least one of the applicants is non-white or hispanic, correspond to columns 1-9.