The Anatomy of Banks' IT Investments: Drivers and Implications

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Abstract

Using a newly compiled measure, this paper studies the determinants and implications of US banks' information technology (IT) investments. Exposure to fintech competition and novel economies of scale are important drivers of the six-fold increase in IT investments observed over two decades. Further analyses point towards significant implications of banks' IT investments for both monetary policy transmission to lending and financial inclusion of low income borrowers.

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

Corbat (2014), Citibank (CEO)

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

Hamers (2017), ING (CEO)

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

Financial Times, January 15, 2022

I. Introduction

The use of technology is transforming the financial services industry. Fintech lenders (henceforth, fintechs) are gaining market share possibly by offering faster and more convenient loan approvals than traditional banks. 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 pronouncements 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? And finally, what are the consequences of such large IT investments in areas that policy makers care about such as monetary policy transmission to credit and financial inclusion of underserved borrowers?

To answer these questions, we construct a novel measure of banks' information technology (IT) spending using textual analysis of publicly available regulatory filings (Call

[1]E.g., see Figure A1.

[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).

reports) for US banks. This measure, building on work by Kovner, Vickery, and Zhou (2014), improves on previous ones which mainly rely on indirect measurement or proprietary survey data or include spending beyond IT (Section II and Subsection III.C discuss in detail the improvements over previous measures). Moreover, our measure is built from non-confidential data, making it available for free to other researchers.

Using our novel measure, we first confirm that banks' IT expenses have increased tremendously. In nominal terms, they were 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 expenses has been heterogeneous. While the share of IT to overall expenses a decade ago was similar for large banks relative to their smaller counterparts, the former have 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, Fedyk, He, and Hodson, 2024).

We explore the role of a host of factors in explaining cross-sectional differences in banks' IT spending. First, we exploit variation in banks' exposure to early fintech mortgage lenders (i.e. companies that allow for a fully online mortgage origination) to test whether competition from fintech lenders propelled banks (especially larger ones) to increase their investments in technology. We find that banks more exposed to fintech competition invest more in IT. We also adopt an instrumental variable (IV) 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. IV estimates confirm OLS findings.

We analyze the correlation of banks' IT investments with the characteristics of the counties where the banks operate and collect deposits. We find that banks that operate in poorer counties adopt more IT, consistent with evidence–discussed below–that less well-off customers are more likely to rely on fintechs or high IT banks for mortgages (or, equivalently, that more IT is needed to serve less well-off customers). We also find that 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. We also find that banks operating in counties with an older population invest less in IT, which can be driven by younger customers and/or younger employees being more IT-savvy. We do not detect any significant role for either broadband access or local bank concentration in driving IT expenses. Regarding banks' business model, we find that banks that earn a larger share of income from non-interest sources and have more deposits also spend more on IT, suggesting that IT can help banks better serve their depositors and earn fees on different products.

We then turn to the potential consequences of banks' IT adoption focusing on two policy-relevant margins. We study whether banks that invest more than others in IT respond differently to monetary policy shocks and whether they cater differently to those borrowers that are often excluded from mortgage markets.

Recent changes in the financial intermediation landscape—such as the rise of fintechs and other non-banks—have influenced the transmission of monetary policy to credit provision (Chakraborty, Goldstein, and MacKinlay (2018), Agarwal, Hu, and Zheng (2023), Elliott, Meisenzahl, Peydró, and Turner (2022)). Banks' IT investments may further shape their responsiveness to monetary policy shocks. On one hand, IT can enhance market power—for example, through superior digital services—reducing the elasticity of loan demand and dampening the response of credit to interest rate changes. On the other hand, by lowering operational costs such as administrative expenses, IT may increase the sensitivity of credit supply to funding costs. Exploiting high-frequency monetary policy shocks around Federal Reserve announcements, we show that the effects of unexpected monetary tightening vary by IT intensity: high-IT banks reduce lending less and raise rates more in response to tightening, consistent with lower demand elasticity among their borrowers.

We also examine the implications of banks' IT investments for financial inclusion—a relationship that is ex-ante ambiguous. On one hand, IT may enhance inclusion by facilitating remote access, reducing operational costs, and potentially mitigating income- or race-based discrimination through standardized processes. On the other hand, IT-driven models may overlook soft information critical for assessing underserved borrowers, and may perpetuate existing biases embedded in data. Prior studies are mixed: some find fintechs improve access for underserved communities (Buchak, Matvos, Piskorski, and Seru (2018), Erel and Liebersohn (2020)) while others show that algorithmic lending can sustain discrimination (Bartlett, Morse, Stanton, and Wallace (2022)).

To explore this relationship, we merge Call reports with HMDA mortgage data, focusing on residential mortgage lending—an area where inclusion matters for wealth-building and where fintech presence is prominent. Lenders are categorized as high IT banks or low IT banks (based on the five-year average ratio of IT to non-interest expenses), non-banks, or fintechs. We find that fintechs and non-banks attract more applications from lower-income and minority borrowers compared to low IT banks. High IT banks also receive more applications from lower-income borrowers (controlling for location), though less so than fintechs or non-banks, and have similar minority applicant shares as low IT banks. In terms of outcomes, high IT banks have similar overall acceptance rates but are more likely to approve applications from low-income borrowers—mirroring the behavior of fintechs and non-banks. Yet, they do not show greater inclusion of minority applicants, a gap that fintechs and non-banks help close.

This collection of findings suggests that a more IT intensive banking sector may affect monetary policy transmissions while also fostering financial inclusion of lower income borrowers. We do not find evidence, instead, of improved access to credit for minority borrowers.

Related Literature

This paper contributes to the literature on technology adoption by banks. Berg, Burg, Gombović, and Puri (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, Rainone, and Supino (2021), Dadoukis, Fiaschetti, and Fusi (2021), Kwan, Lin, Pursiainen, and Tai (2024), Pierri and Timmer (2022)).[3] Other papers have studied the impact or the determinants of different technological innovations (such as ATM, online banking, or high-speed internet) in banking (Hannan and McDowell (1987), Berger (2003), Bofondi and Lotti (2006), Hernández-Murillo, Llobet, and Fuentes (2010), Bostandzic and Weiss (2024), D'Andrea and Limodio (2019)) while some recent contributions focus on the connection between IT in banking and credit to small firms or startups (Ahnert, Doerr, Pierri, and Timmer (2021), He, Jiang, Xu, and Yin (2021)) or use measures of consumer-facing technology to measure IT's impact on competition, deposit stickiness, and small business credit (Koont (2023), Koont, Santos, and Zingales (2024), Core and De Marco (2024)). The risks created by cyber-attacks to financial institutions have also been the object of recent studies (Kotidis and Schreft (2022)). We contribute to the literature by building a new measure of US banks' IT spending from regulatory filings, studying its determinants (in particular the role of fintech competition), and analyzing the impact on banks' lending behavior and responsiveness to monetary policy shocks.

A growing literature highlights that financial intermediaries and their characteristics matter for the transmission of monetary policy (Chakraborty, Goldstein, and MacKinlay (2020), Li (2022), Agarwal et al. (2023), Elliott et al. (2022)) For instance, Hasan, Kwak, and Li (2024) document that the transmission of monetary policy to credit and the real economy is more muted in Chinese provinces with larger fintech market shares. We contribute to this literature by presenting bank-level evidence on the role of IT investments.

Closer to our paper are recent studies investigating the role of online banking on the transmission of US monetary policy to deposit rates and flows. Erel, Liebersohn, Yannelis, and Earnest (2023) document that "online bank deposits experience inflows, while traditional banks experience outflows during monetary tightening in 2022" as online banks increased rates more swiftly after monetary tightening. On the other hand, Koont et al. (2024) find that banks with

[3]Jansen, Nagel, Yannelis, and Zhang (2025) show that increased data availability can lead to increases in total social welfare.

stronger online banking capabilities experience larger outflows of deposits (and higher costs of funds) when the Fed funds rate increases. We complement this literature by presenting empirical evidence regarding the impact of overall bank IT investments, rather than online banking specifically. As IT is a general purpose technology, the impact of specific technological applications may differ from the overall impact of a more IT-intensive financial sector.[4] Moreover, we focus on credit provisioning and costs rather than on deposits.

Previous literature documents several benefits of fintech lending (Berg, Fuster, and Puri (2021)). For instance, Fuster, Plosser, Schnabl, and Vickery (2019) find a 20 percent improvement in processing time in the context of US mortgage lending. Many studies document benefits for financial inclusion: fintechs lend more to underserved borrowers and communities (Erel and Liebersohn (2020), Dolson and Jagtiani (2021), Jagtiani, Lambie-Hanson, and Lambie-Hanson (2021)) and are less likely to discriminate against minority borrowers (Howell, Kuchler, Snitkof, Stroebel, and Wong (2021), Bartlett et al. (2022)). We contribute by showing that high IT banks also lend more to poorer borrowers, although not to racial minorities. This paper is also related to the work by Buchak et al. (2018), showing that the rapid rise of non-bank financial intermediaries in US mortgage origination, including fintech lenders, is mostly related to regulatory arbitrage while technological advantage is a less important factor. Though our results are consistent with these findings, we also find that the presence of fintech lenders spurred IT adoption by banks.

The rest of the paper is organized as follows. Section II describes the data. Section III provides summary statistics and stylized facts for the key variables in our analysis. Section IV examines the drivers of banks' IT adoption. Section V investigates the consequences of banks' IT investments for monetary policy transmission and financial inclusion. Section VI concludes.

[4]For instance, Pierri and Timmer (2022) document that banks with higher pre-GFC IT adoption were more resilient during the crisis, despite previous literature highlighting that some specific technological innovations, such as certain default prediction models (Rajan, Seru, and Vig (2015)) led to higher risks.

II. Data

Bank data and IT expenses. Call reports are quarterly regulatory filings submitted by commercial banks in the US to the Federal Financial Institutions Examination Council (FFIEC) and audited by the Federal Deposit Insurance Corporation (FDIC). Unfortunately, banks are not specifically required to report IT investments or expenses.[5] However, banks report the top (up to) three items within non-interest expenses that are not otherwise itemized and represent at least 10 percent of the unclassified non-interest expenses.[6] We find that from 2001-2021, 68.5% of the filings report something in these unclassified non-interest expenses. 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 an "IT expense" if its description contains any IT-related keyword such as "software", "computer", or "internet".[7]

Introducing and describing this measure of IT expenses[8] 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), and Lewellen and Williams (2021). This approach is better

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

[6]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.

[7]The full set of keywords includes "web", "software", "IT " (e.g., IT services), "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 thousand descriptions of banks' expense items.

[8]Our new measure does not capture the wages paid to IT personnel directly, but can capture IT training, consulting, etc., as long as such expenses are large enough.

[9]Data can be downloaded at http://www.nicolapierri.com

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 (Beaudry, Doms, and Lewis (2010), Bloom, Sadun, and Van Reenen (2012)). Recent papers have relied on the same approach to study IT adoption of financial intermediaries (Ahnert et al. (2021), He et al. (2021), Kwan et al. (2024), Pierri and Timmer (2022)). However, information extracted from regulatory filings is likely to be more reliable 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, Aberdeen data appear to be mostly imputed during the most recent survey waves–using a proprietary and undisclosed imputation procedure–and therefore are not appropriate for any bank-level analysis focused on very recent years (Benmelech, Yang, and Zator (2023), Cao and Iansiti (2021)).

The main downside of our measure is that it underestimates the actual amount of IT expenses for two reasons. First, some expenses 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 expense may not be reported because it does not meet the criteria of being among the

[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 (Kwan et al. (2024), Pierri and Timmer (2022))

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 types of expenses or income flows are 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 (following Drechsler, Savov, and Schnabl (2017)). 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 divide IT expenses 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.

Mortgage data. Home Mortgage Disclosure Act (HMDA) is a rich dataset containing lender, loan, as well as borrower-level information for a large part of US residential mortgage applications. 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

[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 expenses are, in decreasing order, "correspondent bank fees", "manager training", "vault", "software", "computers". The bank would not report any IT related expenses, even if "software" plus "computers" combined were larger than the other items.

amount, loan type, property type, rate spread, and tract-county of loan-origination. From 2018 onward, it also contains information on 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 collect information on the years 2007-2021,[12] but focus some of the analysis on the period from 2018 on, as several variables of interest were added then.

Fintech classification, local characteristics, and additional datasets. Fintechs are lenders with a strong online presence for which the mortgage application process takes place online with no human involvement from the lender as in Buchak et al. (2018). Following previous literature, we classify a non-bank mortgage originator as a 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 lender is referred to as a non-bank throughout the rest of the paper. We exclude credit unions[13] from the sample because of their different incentives and business models relative to commercial banks and other originators.

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

[12]Because of data quality issues, for certain variables we interpolate 2012 data with 2011 and 2013 values. This has no material impact on our results as no variables from HMDA dataset are used in the panel dimension in our analyses.

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

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).

III. Descriptive Patterns and Comparison with other IT Measures

III.A. IT expenses over time

Figure 1 illustrates the evolution of banks' total IT expenses compared to assets and non-interest expenses.[14] 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 their 2001 values. This is particularly striking because the price of computing power steadily decreased over time (Moore's law), suggesting an even larger divergence in real terms.

[Insert Figure 1 approximately here]

Did all banks adopt 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

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

expenses have gone down in the other size categories.[15] This holds true even if we just include those banks that reported some positive value in the non-interest expense descriptive category (see Figure A2).

[Insert Figure 2 approximately here]

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 their customers 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, Matray, Veldkamp, and Venkateswaran (2022)), which in fact have been investing more in data science and artificial intelligence (Babina et al. (2024)).[16]

A potential concern with these empirical patterns is that large banks may have simply started recording 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, Graph A of Figure 3 shows that other non-interest expenses (that is, non-interest expenses in the descriptive fields of Call reports that do not involve IT related keywords) have been declining over time, and small and large banks follow similar patterns. Moreover, Graphs B, C, and D illustrate the evolution of several important

[15]These patterns are similar if we focus on a balanced panel of banks (Figure A9). Figure A11 shows that the increase in IT investments is much stronger for top 1% banks, while the IT investments of banks in the 2nd to 10th percentile show a pattern in between the top 1% and the other banks.

[16]In this discussion, we infer larger gains from IT for larger banks from the fact that larger banks invest more in IT. An alternative interpretation of this fact could be the growing of presence of diseconomies of scale insofar larger banks have to spend a lot more on IT to produce the same output. We believe that such alternative explanation is unlikely to play an important role. In fact, IT inputs, such as software, are easily scalable (De Ridder (2024)) Moreover, the (arguably) most important evolution for IT during the sample period has been the rise in the importance of data as a source of value in many industries, including finance (Veldkamp (2023)). This suggests larger firms can leverage their more abundant data availability through IT investments to create value.

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.

[Insert Figure 3 approximately here]

To provide further evidence on the role of IT investments compared to other type of expenses, Figure A3 plots the evolution of other types of "other" non-interest expenses, constructed by selecting common words among the text variables, such as insurance, management, ATM, and others. None of the alternative expense categories presents an evolution similar to the one of IT investments, highlighting the specific dynamics of IT expenses.

III.B. Distribution of IT expenses

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 expenses, especially the smaller ones, may not be captured.

[Insert Figure 4 approximately here]

III.C. Comparison with other IT measures

We compare our measure of IT investments with alternative data sources available for US listed banks. Capital IQ Pro dataset contains a *Tech & Communication Expense* for publicly listed companies, which is defined as: "Expenses paid for communications, data processing and technology such as computers, software, information systems and telecommunications". We perform the same comparison with an IT investments measure constructed from survey data provided by Aberdeen and used in recent literature on IT in banking (Ahnert et al. (2021), He et al. (2021), Kwan et al. (2024), Pierri and Timmer (2022)). Capital IQ Pro is merged to Call reports through the parent bank holding company (BHCID). Aberdeen data are merged with Call reports by bank names, as detailed in Pierri and Timmer (2022). We are able to merge 412 banks for the year 2019 across the three datasets.

Figure A6 shows that our IT measure is positively correlated with the Capital IQ Pro tech measure, whereas the Aberdeen measure is not.[17] This lack of correlation could be due to imputation in the recent years in the Aberdeen dataset, on top of the difficulties in merging different datasets using banks' name. These results suggest that empirical studies aimed at studying the drivers or implications of banks' IT adoption are better off relying on data from regulatory filings than on survey data.

One caveat with using the Capital IQ Pro measure is that the variable captures a broader class of expenses than our IT variable. In fact, while we aim to narrowly capture investment in IT, the Capital IQ Pro variable also includes expenses for traditional communication (e.g., telephone, fax, mail, etc.) and expenses for external data processing. These expenses are separately identifiable in Call reports. We find that these tech expenses exhibit different patterns than more narrowly defined IT expenses: for instance, Capital IQ Pro tech expenses over assets are negatively correlated with size in the cross-section and are mostly stable over time–at least from 2015 onward (Figure A5). This result is possibly driven by telecommunication and data processing expenses reported in the Call reports, which exhibit the same pattern (Figure A7). Telecommunication and data processing expenses are substantial and can also help reconcile the fact that the Capital IQ Pro tech measure is much larger than our IT measure in Figure A6. We replicated our analysis of determinants of IT spending in banking (Section IV) for Capital IQ and the contrast in results is in Table A1. This highlights that researchers should be careful in selecting the measure of interest according to the research question at hand.

A final validation exercise is illustrated by Figure 4. The green dashed lines represent the

[17]Correlation is 6%, although it increases to 44% if only banks with positive IT investments are included.

overall averages, while the red lines report the average for a subset of banks that, in 2019, offered the possibility of fully online mortgage application (as reported by Buchak et al. (2018)). Comparison between the two lines suggests IT investments are instrumental in improving banks' online lending capabilities.[18]

IV. Determinants of IT spending in banking

The previous section illustrated the importance of bank size in explaining IT investments. In fact, in 2019 the correlation between banks' 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 other potential determinants. Our main focus is on the importance of competition from fintech providers in fostering IT adoption and we propose an instrumental variable specification to indicate a causal relationship. The other potential determinants are explored in a descriptive manner. We focus on 2019 as the base year to abstract from the impact of the COVID-19 pandemic on banks' spending. Before discussing the empirical specification and results, we introduce the variables we explore as determinants of banks' IT spending.

Fintech and bank competition. A sizeable literature has studied the relationship between the competitive environment and firms' incentives to innovate or adopt new technologies (Aghion, Bloom, Blundell, Griffith, and Howitt (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' IT investments. For instance, the *Financial Times* reported in January 2022 that

[18]This exercise is also related to recent literature capturing banks' IT through measures of mobile apps or websites quality (Core and De Marco (2024), Koont (2023)), although we focus on the offering of online services rather than the platform quality.

"*JPMorgan plots astonishing $12bn tech spend to beat fintechs*".[19] However, how banks react to digital disruption is an empirical question (Vives (2020)). To empirically investigate the connection between fintech competition and banks' IT expenses, 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 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:

$$ExposureFintech_{b,t} = \sum_{c} \frac{Mortgages_{c,b,t}}{Mortgages_{b,t}} \frac{MortgagesFintech_{c,t}}{Mortgages_{c,t}} \quad (1)$$

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 Herfindahl-Hirschman Index (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' IT adoption is that it can partly substitute for the local presence of physical branches, for instance by helping banks interface with customers through online channels, or more generally diminish the need for human work. We therefore measure branch consolidation with the 5-year growth rate of the number of branches

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

with deposits from FDIC data. The growth is measured with Davis and Haltiwanger (1992) (DHS) growth rates[20] from 2015 to 2019.

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 customers' attitude towards technology or bank costs, altering the benefits of adopting IT, particularly related to front-end processes. For instance, online banking interaction may be favored by borrowers with a 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 technology savvy human capital 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 reasons. IT in banking may be particularly helpful in less densely populated areas of the country. To proxy for some of the effects discussed, we gather county-level information on income, share of minority population (i.e., everyone except for White non-Hispanic), share of adults with tertiary education, median population age, 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 II for data sources).[21] As the dependent variable–IT adoption–is measured 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.

[20]The DHS growth rate is equal to $2 \times \frac{X_t - X_{t-1}}{X_t + X_{t-1}}$ (Davis and Haltiwanger (1992))

[21]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 belongs–rather than county itself–as universities can impact the availability of human capital in the local labor market (Moretti (2004)), and commuting zones are constructed exactly to capture local labor markets.

Bank characteristics. We also include a set of controls for bank characteristics that could also influence banks' IT spending decisions. 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 funding sources. Net income over assets, instead, measures profitability.

Dodd-Frank Act and the cost of compliance. Some of the increase in IT expenses following the GFC might be due to banks' costs of complying with greater post-GFC regulations, such as the Dodd-Frank Act (Hogan and Burns (2019)). The largest banks, in particular, had to comply with stress-test requirements that likely raised IT expenses. As only banks in larger BHC had to comply with these requirements, the correlation between size and IT investments could be capturing different compliance costs. We, therefore, include a binary variable equal to 1 if and only if the bank belongs to a BHC which participated in a Dodd-Frank Act stress test in the previous 5 years.

Empirical Specification. We estimate the following cross-sectional linear regression to examine the determinants of IT spending:

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

where the dependent variable IT_b represents IT expenses (normalized by assets or non-interest expenses), averaged across 2015-2019. We average across 5 years because of the lumpiness in the reporting 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 banks' geographical footprint used to construct the local characteristics variables, are lagged by 5 years so as not to be contemporaneous with the dependent variables (with the exception of log assets, because of the importance of properly controlling for size in explaining IT documented in

Section III). All independent variables are standardized except the binary variable related to Dodd-Frank stress test. Summary statistics are reported in Table A2.[22]

Results. The results of estimating equation (2) by OLS are reported in columns (1) and (2) of Table 1, weighting banks by their loans' values. Large banks have larger shares of IT expenses. A doubling of bank size is associated with an increase of IT expenses which is about half of the sample mean.

[Insert Table 1 approximately here]

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 in column (2): an increase in one standard deviation of exposure to fintech competition is associated with an increase of IT expenses which is about a third of its sample mean (see end of the section for more discussion on the magnitude of the coefficients). Having experienced more intense competition from fintechs could stimulate IT adoption for two reasons: either banks may be 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 benefits of digitalization in banking and thus invested more, even if IT is used primarily with different purposes. In Subsection V.B, we present evidence that the lending behavior of high IT banks–on most dimensions–does not become more similar to that of fintech lenders, suggesting the latter story is more likely than the former.

We do not find that bank concentration explains IT adoption. Most local-level characteristics are also statistically insignificant, with the exception of income, population age, and population density. Banks in areas with lower income individuals tend to invest more in IT.

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

There are multiple potential explanations for this correlation: banks' IT spending may need to be greater to cover increased costs of credit screening and monitoring insofar lower income individuals tend to be riskier; lower income borrowers may prefer high IT banks if these banks provide them with credit relatively more frequently, perhaps because of better risk management. Furthermore, in person interactions in bank branches may be unpleasant for some low-income individuals. In Subsection V.B we rely on mortgage-level data to document that high IT banks both receive more applications from lower income borrowers and are relatively more likely to accept applications from these borrowers.

Furthermore, banks operating in counties with an older population invest less in IT, consistent with younger people being the early adopters of IT technologies, both as banks' clients and as workers (Meyer (2011)). Furthermore, banks operating in counties with lower population density also invest more in IT, perhaps because of the higher value of reaching customers further away from bank branches (consistent with results on online banking and "banking deserts" by Dante and Makridis (2021)). We do not find a significant correlation with local access to broadband.[23]

Banks with lower profits in the past also spend more on IT, perhaps because of the need to improve their cost structure.[24] 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 other than lending, such as interacting with depositors through online channels.

The coefficient of Dodd-Frank stress tests is positive but not statistically different from

[23]While this result may be surprising, it is also in line with some of the previous literature: Fuster et al. (2019) document no correlation between fintech lending and local Internet usage or speed and confirm these null results using the entry of Google Fiber in Kansas City as a natural experiment.

[24]Banks that reduce more the number of physical branches also invest more in IT, but the coefficients are not statistically different than zero at 10 percent confidence levels. Thus, there is inconclusive evidence on whether IT adoption is used to substitute for physical presence for cost savings purposes.

zero, providing inconclusive evidence on the role of compliance requirements in spurring IT investments. Below, we rely on within-bank variation to provide more detailed evidence.

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 binary variable indicating 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 refer to large banks as those in the top 20 percent while columns 2 and 4 refer to large banks as those in the top 10 percent. Focusing on the variables that are significantly associated with IT investments in Table 1, we find that fintech competition has a larger and more robustly significant impact on IT adoption among large banks, while these banks are less likely to increase IT spending in areas with higher income per capita. IT spending among large banks also increases more with higher deposit funding and a higher share of non-interest income, suggesting that large banks may increase IT spending to better serve their depositors and conduct non-lending activities.

[Insert Table 2 approximately here]

Bivariate Regressions. Our main empirical specification, equation (2), includes a large number of potentially correlated regressors. To test the sensitivity of the estimations to the inclusion or exclusion of different controls, we also present a set of bivariate regressions of IT investments on each single variable of interest, including log assets as the only control. Results, shown in Table 3, are remarkably robust: all coefficients that are statistically different than zero in the multivariate regression (Table 1) are also different than zero and have the same sign in the set of bivariate regressions. This exercise provides reassurance that none of the results discussed above are driven by a particular choice of controls.

[Insert Table 3 approximately here]

Poisson regressions. OLS estimates may have undesirable properties when the dependent variable has a very skewed distribution (Cohn, Liu, and Wardlaw (2022)), as is the case for bank's IT investments (see Figure 4). Some authors suggest that the Poisson regression model–which deals with count dependent variables–can be employed to overcome these problems even when the dependent variable is continuous (Silva and Tenreyro (2006), Cohn et al. (2022)). We therefore re-estimate equation (2) with a Poisson regression model through log-likelihood. The results, presented in Table A3 , are reassuring: all the determinants that are (are not) statistically different from zero in the OLS specification are (are not) also different from zero, and have the same sign, when the Poisson model is estimated. Thus, we conclude that our empirical results are robust to biases that could be introduced by applying OLS to skewed outcome variables.

Dodd-Frank stress tests in the panel dimensions. We also adopt an alternative approach to further investigate the relationship between Dodd-Frank stress tests and IT investments, in order to shed light on the role of compliance requirements. We estimate panel regressions at the bank-year level, where the dependent variable is the IT investments, scaled by assets or non-interest expenses, in a given year, while the independent variable is a binary variable indicating whether the banks' group was required to undergo a Dodd-Frank stress test during the same year. Controls are year and bank fixed effects. This specification leverages the fact that different BHC have different requirements in terms of the timing of stress tests according to their size (and the size thresholds have been changing over time). We find that banks invest more in IT during the Dodd-Frank stress years than in other years (see Table A4), although this is partly explained by the fact that larger banks adopt more IT over time and are also more likely to be subject to Dodd-Frank stress tests.

IV.A. Instrumenting exposure to fintech competition.

Banks which were more exposed to competition from fintech mortgage originators in the early phase (2010-2015), also end up spending more on IT. This relationship could arise because of a causal impact of fintech exposure on banks' IT or because of reverse causality or correlated confounding factors. For instance, a potential concern with a causal interpretation of the results is that greater bank IT spending may increase their shares of mortgage originations and therefore reduce the market shares of fintech firms. Under this scenario, fintech market share would be endogenous to banks' IT. Another concern is that banks and fintechs that compete in the same local markets may be trying to cater to similar "IT loving" borrowers. We describe an instrumental variable strategy to address these concerns.

The history of the most important fintech mortgage lender in the US provides an empirical strategy to disentangle the two stories. Quicken Loans (Rocket Mortgage since 2018) was founded under 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 quickly in the aftermath of the GFC to become the largest US mortgage originator in 2018.[25]

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 (company's nonfinancial 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 2010s. 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 follow the law of gravity (Blum and Goldfarb (2006)). Figure 5 indeed reveals a positive

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

correlation between the share of deposits that a bank had in Michigan in the 2010-2015 period and the exposure to fintech competition in the same period.[26]

[Insert Figure 5 approximately here]

We therefore re-estimate 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 than Michigan itself. Results are presented in Table 4. 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 where IT expenses are a ratio of assets and non-interest expenses, respectively. 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) demonstrate that the results do not depend on the inclusion of controls.

[Insert Table 4 approximately here]

An important concern with these estimates is that the first stage t-statistics of the exogenous instrument is less than 4. Moreover, we obtain a much larger IV coefficient than OLS. These two elements indicate the presence of a weak-instrument problem.[27] Therefore, we apply weak instrument techniques following Andrews and Stock (2018). Rather than producing point

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

[27]The IV coefficient could be larger than the OLS also for another reason. If bank IT spending also reduces fintech market share, thanks to the bank's improved ability to capture shares of the mortgage market, it would seem to reduce the positive relationship between the two variables.

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 (Andrews and Stock (2018), Andrews, Stock, and Sun (2018)), we construct such confidence interval by relying on a version of the Anderson and Rubin test (Anderson and Rubin (1949)) which allows for non-homoskedastic standard errors. Table 4 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.

If the relationship between Michigan deposits and IT adoption is indeed driven by fintech competition–which is our exclusion restriction–we would expect the relationship to be stronger for banks that rely more on mortgages as a source of income. Furthermore, given the importance of economies of scale documented above (Table 1 and Table 2) we would expect larger banks to be better equipped to respond to such competitive threats. Therefore, we augment the reduced form equation–the regression of the dependent variable (IT adoption) on the instrument (Michigan deposits)–with the interaction terms between Michigan deposits and mortgage reliance (the share of net income coming from real estate lending) and bank size. The results are presented in tabular form in Table A5, which shows the effect of Michigan exposure on IT investments for different levels of the interaction variables: the relationship between Michigan deposits and IT is significantly stronger for larger banks, providing indirect support for the instrument's exclusion restriction. It is not statistically significantly larger for banks which rely more on mortgage lending as a source of income: while the interaction coefficients are positive, t-stats are below 0.5.[28]

[28]This lack of statistical significance could be driven by several factors: (i) noise in the data; (ii) the possibility that banks exposed to fintech through their Michigan footprint could have observed the benefits of a more IT-heavy delivery of financial service even when their business model overlaps with fintech only partially; and (iii) omitted variables that may independently induce Michigan banks to invest more in IT.

A final concern is that something special about the Michigan area or the Great Lakes region could have both propelled Rocket Mortgage success and banks' IT adoption. However, in Table A6 we document that neither the shares of deposits in the bordering states of Indiana, Ohio, and Wisconsin, nor the shares of deposits in the close-by Great Lakes states of Illinois and Minnesota[29] predict subsequent IT adoption, thus mitigating this concern.

Back of the envelope calculation of the impact of fintech competition on bank IT spending. 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.

As the OLS coefficients are within the boundaries of the Anderson and Rubin confidence intervals, the IV approach does not reject the null of no endogeneity of the regressor of interest. Thus, we rely on OLS coefficients to gauge the magnitude of the impact of early fintech exposure on IT expenditure. We multiply the OLS coefficient by the standard deviation of fintech exposure (2 percentage points, see Table A2). We then compare this quantity with either the standard deviation of the IT measure in the sample (see Table 1) or with the change in the IT measures over the 20 sample years (2021 vs 2001) for the average bank. The estimated impact of a one-standard deviation higher early fintech exposure leads to higher IT expense equal to 17% of the sample standard deviation (results are similar if we consider IT normalized by assets or non-interest expenses), or also equal to 90% of the change in IT expenses over assets (70% of the change in IT expenses over non-interest expenses) over the sample period.

[29]New York is also a Great Lakes state, but it is home to the main US financial center, and thus excluded by this placebo test.

V. Implications of IT investments

To shed light on the potential consequences of a more technology centered financial industry–as captured by the six-fold increase in IT investments documented in Section III–this section investigates how banks with heterogeneous degrees of IT investments differ in two policy-relevant dimensions: the response on the lending side to monetary policy shocks (Subsection V.A) and the financial inclusion of low-income and minority borrowers (Subsection V.B).

V.A. 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 intensive financial system. To provide evidence in this regard, we study how banks' lending response to monetary policy shocks depends on their past IT spending.

There are different reasons why IT spending may impact the transmission of monetary policy on the lending side. 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 the prices of its services (in particular, loan rates) in response to changes 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. If these supply side factors are prevalent, we expect high IT banks to respond to a monetary tightening (loosening) by increasing (decreasing) loan rates more and decreasing (increasing) loan quantity more as well.

On the other hand, demand factors may lead to different results. IT investments are often linked to higher firm market power (Foster, Haltiwanger, and Tuttle (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 monetary tightening–would lead to a larger change in prices and smaller one in quantities with respect to low IT banks. Moreover, market power in banking is often found to decrease the transmission of monetary policy to credit (Scharfstein and Sunderam (2017), Benetton and Fantino (2021)). Therefore, how IT interacts 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. Our time period is from 2002Q1 (around 8000 banks) to 2019Q3 (around 5000 banks). We use the local projection method by Jordà (2005) and first estimate the following set of linear regressions:

$$\Delta^h \log Y_{b,t} = \delta_b + \beta^h MP_{t-1} + \gamma X_{b,t} + \epsilon_{b,t} \tag{3}$$

where $\log Y_{b,t}$ is an outcome of interest for bank b's 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 (3) 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% and 95% confidence interval, is presented in Figure 6. This figure 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).

[Insert Figure 6 approximately here]

To understand whether the impact of monetary policy is different depending on a bank's IT spending, we estimate the following augmented set of regressions:

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

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 $X_{b,t}$, we also include (with a one-year lag) the time varying bank-level variables discussed in Section IV: 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 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 also included without the interaction term.)

The coefficients α^h, together with 90% and 95% confidence intervals, are reported in Graphs A and B of Figure 7 (also in Table A7 and Table A8). The coefficients in both graphs 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, Graphs C and D plot the estimated cumulative impulse response function to a 100 basis point unexpected monetary tightening for banks with half a standard deviation IT expenses above and below the mean. These two banks differ by one standard deviation of IT investments. When we focus on loans (Graph C) their response function is quite different: the trough of the bank with lower IT expenses is more negative by a third with respect to the trough of the bank which invests more in IT. The two impulse response functions are, instead, less different when we focus on interest earned (Graph D).[30]

[Insert Figure 7 approximately here]

As discussed above, these findings can be rationalized as high IT banks facing a less elastic demand curve, in line with previous literature arguing IT investments are connected to greater market power. (Figure A13 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 banks adjust credit less than other banks is that these banks are also less financially constrained. In fact, while Section IV 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 a larger size are likely associated to more

[30] Figure A12 presents the same patterns as the Graphs A and B of Figure 7, normalizing IT by assets rather than non-interest expenses. While the qualitative dynamics are unchanged, the magnitude of the coefficients is of course much larger as IT expenses over assets are almost two orders of magnitude smaller than IT expenses over non-interest expenses

stable funding. However, if IT were 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 could provide after a monetary contraction, but they faced a downward sloping demand, then they would provide such credit at higher rates.[31] Furthermore, we augment equation (4) by the interaction between monetary policy shocks and (lagged) deposits over assets, log assets, capital over assets, and securities over assets [32]. As reported by Figure A14, we find qualitatively similar results (smaller in magnitude than those reported by Figure 7 but within the confidence intervals).

V.B. Financial inclusion

Fintech providers (and other non-bank financial intermediaries) have been shown to play an important role for the financial inclusion of low-income and racially defined minority borrowers in US credit markets (Buchak et al. (2018), Erel and Liebersohn (2020)). To understand whether IT in banking is also likely to lead to similar benefits, we study the differences in mortgage applications and acceptance rates between high IT banks, low IT banks, fintechs, and non-banks for different types of borrowers. A bank is classified as a high IT bank for a given 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.[33] Our period of analysis includes the years between 2018 and 2021, since it was during this period

[31] 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 controlling for borrower mix.

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

[33] Given the skewness in the distribution of IT expenses, any bank with positive IT investment is classified as high IT. The low IT group is larger than the high IT. We find a similar pattern when using the continuous variable (IT

that fintech lenders were established as market participants and the HMDA dataset contains richer loan-level information from 2018 onwards.

Application-level analysis. We estimate the following linear regression to examine the characteristics of mortgage applicants to high IT banks relative to other banks and non-banks (especially fintechs):

$$Y_{ilzt} = \beta \text{Class}_{lt} + \gamma X^1_{izt} + \zeta X^2_{lt-1} + \delta_{zt} + \epsilon_{ilzt} \tag{5}$$

where Y_{ilzt} is either the log income of the main borrower applicant or a binary variable indicating whether at least one of the applicant is a minority (non-white or hispanic) in reference to application i to lender l in county z at year t, Class_{lt} refers to the class of lender: low IT bank (base), high IT bank, fintech or non-bank, X^1_{izt} are the application 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 [34]. All standard errors are clustered at the lender level.

We estimate equation (5) including all loan applications originated and rejected (but exclude withdrawn applications). Results, presented in Table 5, reveal that when we control for the county where the property is located, high IT banks, fintechs, and non-banks all receive more applications from lower income borrowers with respect to low IT bank. Fintechs and non-banks also receive more applications from minority borrowers, while we find no similar differences between high- and low-IT banks.

[Insert Table 5 approximately here]

expenses over non- interest expenses) rather than a dummy for high IT banks. The results of this section are also similar if we normalize IT expenses by assets, but they are not reported for brevity.

[34] HOEPA status indicates whether a mortgage loan is a "high-cost mortgage" under federal law.

Acceptance probability. We then analyze how the probability of accepting a mortgage application changes with borrower and lender characteristics. We rely on a linear probability model:

(6)

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

where $Accept_{ilzt}$ is a dummy for whether the loan application i was accepted, Class_{lt} is the class of lender (high IT bank, fintech or non-bank, while low 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.

Results are presented in Table 6. 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. Column (3) reports that low IT banks accept more applications from high income applicants, but the reverse is true for the other lender types. Fintech and non-banks are also more likely to accept applications from minority applicants, while banks are not.

[Insert Table 6 approximately here]

In summary, we observe that banks with high IT capabilities receive more mortgage applications from lower-income prospective borrowers. Additionally, these banks are relatively more likely to accept such applications. It is important to note that the observed negative correlation between a bank's IT level and the income of applicants does not necessarily mean that these lower-income borrowers prefer loans from banks with high IT. Instead, this correlation may be primarily due to the increased likelihood of being approved for loans at these institutions. Nevertheless, these findings indicate that there are some benefits for financial inclusion of borrowers with lower income.

Finally, we find no significant differences across low and high IT banks when examining the race of applicants.

VI. Conclusion

This paper studies the drivers and consequences of bank IT adoption, using a newly created measure of IT spending 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 is positively associated with banks' IT investments, especially for the large banks.

Turning to the consequences of banks' IT adoption, we find that IT investments have implications for the transmission of monetary policy to credit. Banks that invest more in IT reduce their lending by less in response to a contractionary monetary policy shock, but also increase lending rates by more, consistent with them facing a lower residual demand elasticity, relative to low IT banks.

In terms of the impact of banks' IT investments on financial inclusion, we find that banks that invest more on IT, like fintechs, receive more applications and provide more credit to lower income borrowers, relative to low IT banks. However, we do not find differences in the extent to which they cater to racial minorities.

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FIGURE 1

Total assets, non-interest expenses, IT expenses of US banks

This figure plots total assets, non-interest expenses, and our measure of IT expenses for US banks from Call reports normalized by dividing by the 2001 value (so that 2001 = 100).

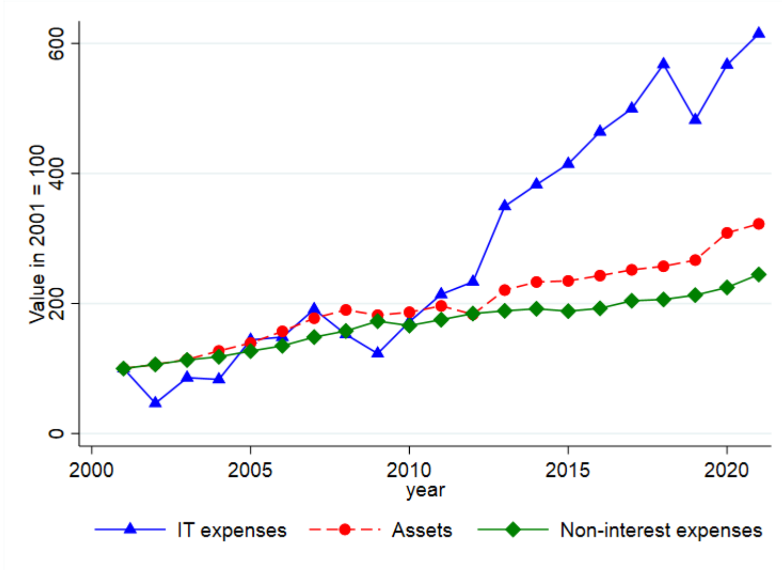
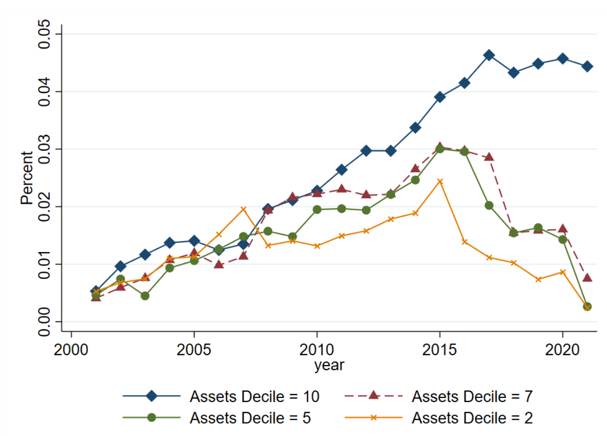


FIGURE 2

IT expenses over time by bank size

The figure shows the average (non-weighted) IT expenses over assets (Graph A) and over non-interest expenses (Graph B) for US banks according to bank size (decile of assets) where "Asset Decile=10" is the top decile.

Graph A. Normalized by assets



Graph B. Normalized by non-interest expenses

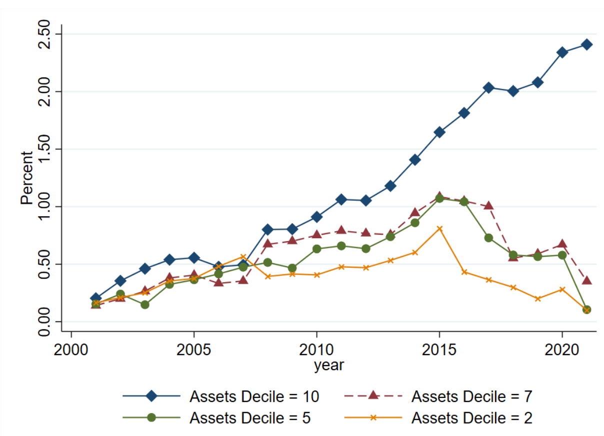
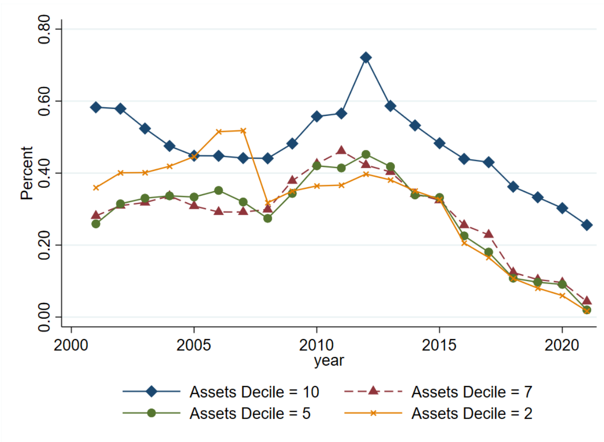


FIGURE 3

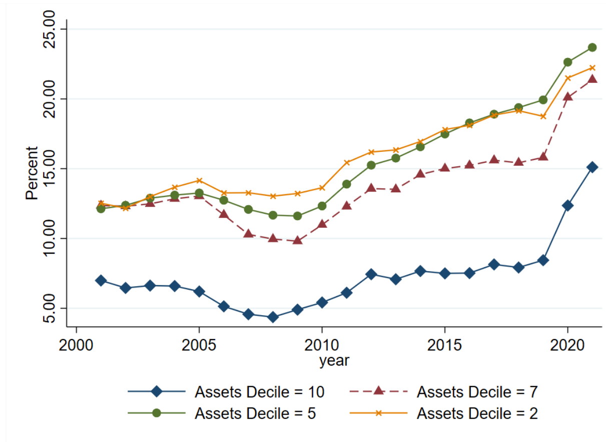
Other non-interest expenses, deposits, loans, and capital over time by bank size

The figure shows the evolution of the (non-weighted) average of different balance sheet items over time, normalized by assets, by bank-size category where “Asset Decile=10” is the top decile. Specifically Graph A refers to non-interest expenses which are classified with descriptions that do not involve IT related keywords.

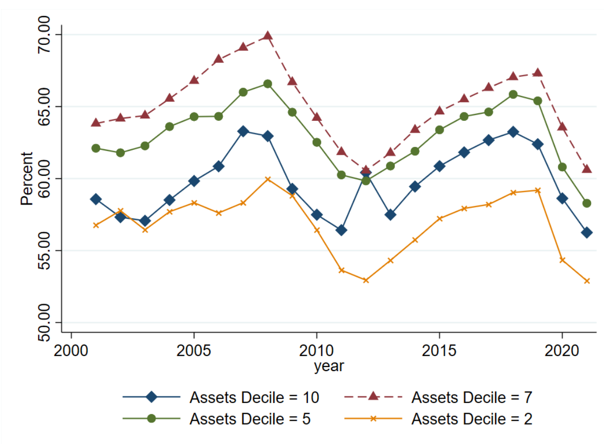
Graph A. Other non-interest expenses



Graph B. Deposits



Graph C. Loans



Graph D. Equity

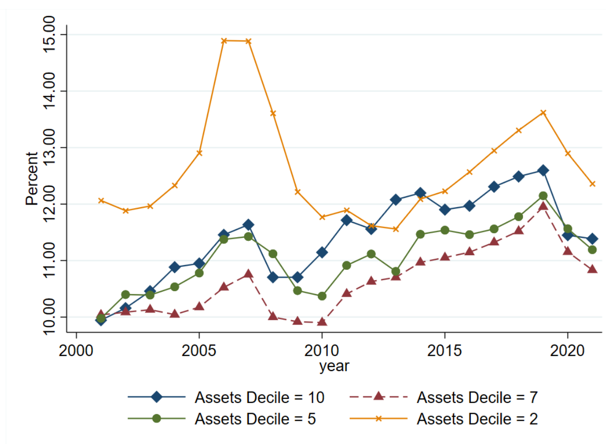
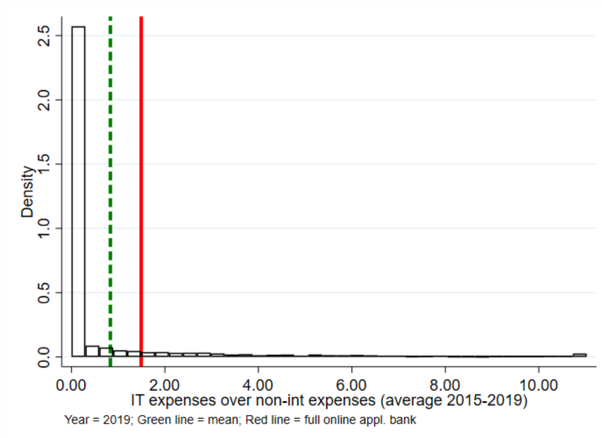


FIGURE 4
IT expenses normalized by non-interest expenses (2015-2019) in percent

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 offered the possibility of fully online mortgage application.

Graph A. Unconditional



Graph B. Conditional on positive IT expenses

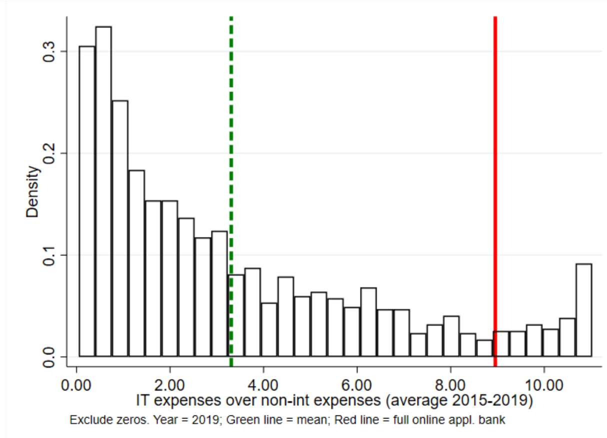


FIGURE 5
Share of deposits in Michigan and exposure to fintech competition

This figure plots a binscatter of the share of deposits in Michigan (measured as a fraction between 0 and 1) against a bank's exposure to fintech competition (average 2010–2015).

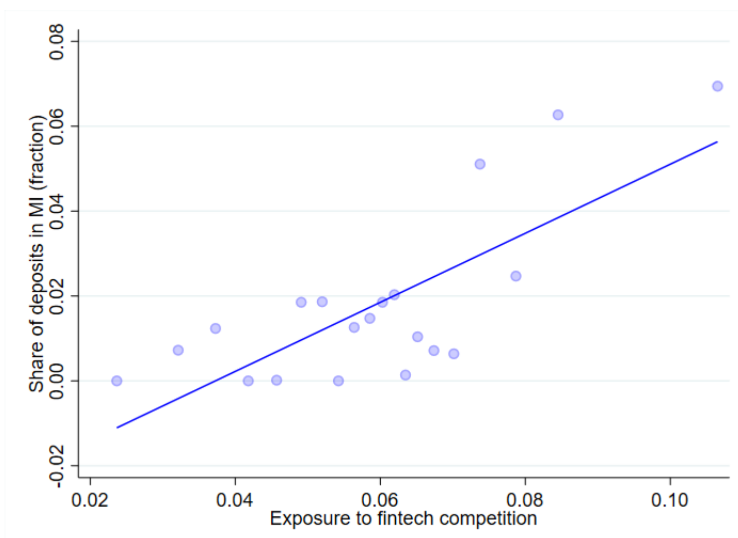


FIGURE 6

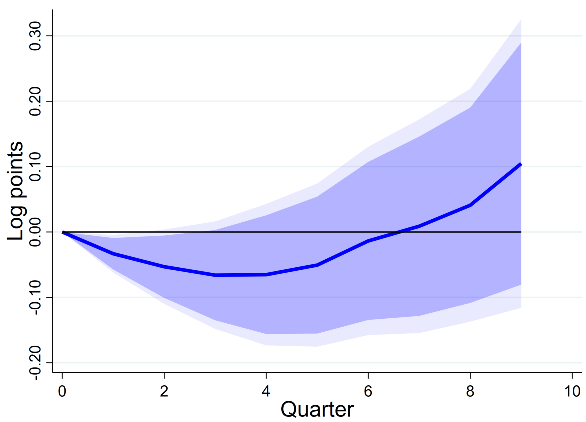
Bank loans' response to a monetary policy shock

This figure plots cumulative impulse response functions (IRFs) of US banks' loans and interest income on loans to a 100 basis point monetary policy shock, estimated using the shock series of Jarociński and Karadi (2020). IRFs are obtained from panel data local projections

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

where $Y_{b,t}$ denotes (i) loans and (ii) interest income on loans over loans for bank b in quarter t, and $\Delta^h \log Y_{b,t} = \log Y_{b,t+h} - \log Y_{b,t-1}$. δ_b denotes bank fixed effects, MP_{t-1} is the monetary policy shock, and $X_{b,t}$ is a vector 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 trace out the cumulative IRF. Observations are weighted by loans. Standard errors are double-clustered at the bank and quarter levels. Shaded areas indicate 90% and 95% confidence intervals. Time period is from 2002Q1 (8K banks) to 2019Q3 (5K banks).

Graph A. Loans



Graph B. Interest Earned on Loans

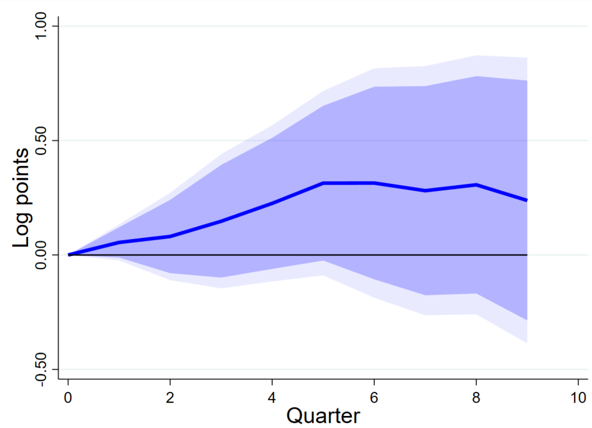


FIGURE 7

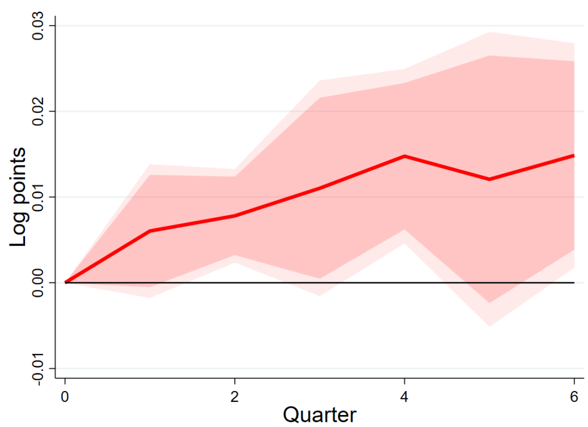
Bank loans' response to monetary policy: IT heterogeneity

Graphs A and B plot the estimated interaction coefficients α^h from the panel data local-projection

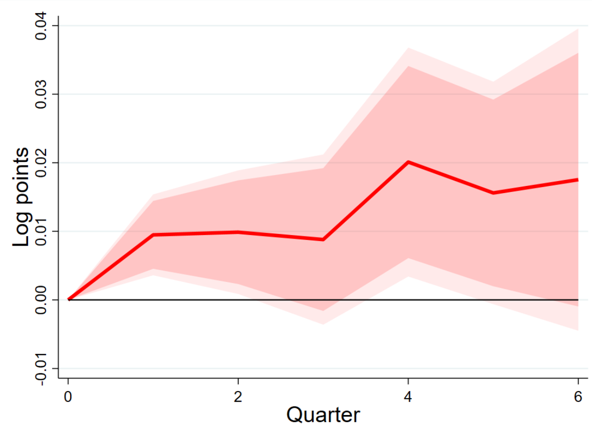
$$\Delta^h \log Y_{b,t} = \delta_b + \zeta_t + \alpha^h MP_{t-1} \times IT_{b,y(t-4)} + \gamma X_{b,t} + \varepsilon_{b,t},$$

where $Y_{b,t}$ denotes bank b's loans (Graph A) or interest income on loans over loans (Graph B) in quarter t, and $\Delta^h \log Y_{b,t} = \log Y_{b,t+h} - \log Y_{b,t-1}$. MP_{t-1} is a monetary policy shock from Jarociński and Karadi (2020); $IT_{b,y(t-4)}$ is the bank's average IT expenditure over the previous five years, normalized by non-interest expenses. δ_b and ζ_t denote bank and quarter fixed effects, and $X_{b,t}$ is a vector of time-varying controls which includes lagged (by on year) time-varying bank variables such as equity, deposits, net income, loans normalized by assets, share of non-interest income, and log of assets. Observations are weighted by loans. Standard errors are double-clustered at the bank and quarter levels. Shaded areas indicate 90% and 95% confidence intervals. Graphs C and D plot cumulative impulse response functions to a 100 bp monetary tightening for banks with high (0.5 sd above the mean) and low (0.5 sd below the mean) IT expenditure. Time period is from 2002Q1 (8K banks) to 2019Q3 (5K banks).

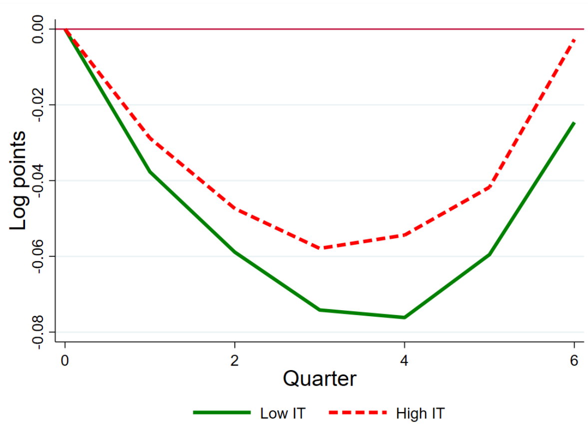
Graph A. Loans: Interaction term



Graph B. Interest Rate Earned on Loans: Interaction term



Graph C. Loans: IRF of High vs low IT



Graph D. Interest Rate on Loans: IRF of High vs low IT banks

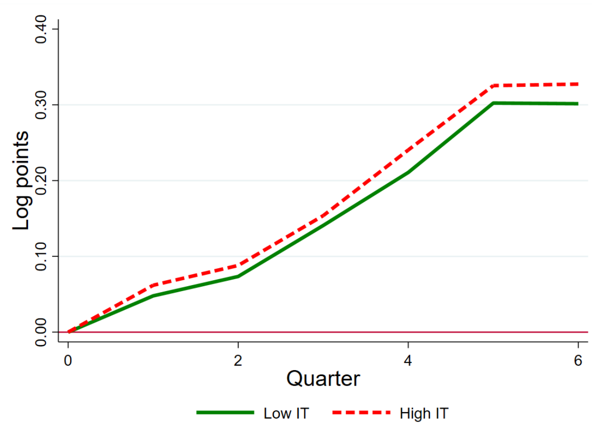


TABLE 1

Determinants of banks' IT adoption

Results of estimating the following cross-sectional equation: $IT_b = \alpha + \beta X_b + \epsilon_b$ where b is a bank. IT_b are IT expenses normalized either by assets (1) or by non-interest expenses (2), averaged across 2015-2019. X_b is a set of bank-level controls including log value of assets, dfast (a dummy equal to one if the bank participated in a Dodd-Frank Act stress test), fintech exposure from 2010-2015, 5-year Davis and Haltiwanger (1992) growth of the number of branches with deposits from 2015-2019, county-level local characteristics such as the median age, share of STEM among graduates from universities in the commuting zone, math scores of graduates from universities in the commuting zone, Herfindahl-Hirschman Index (HHI) of deposits, share of adults with tertiary education, income per capita, population density, share of population with access to broadband connection of at least 25 Mbps and share of minority population (non-white or Hispanic), and bank-level characteristics such as share of loans over assets, share of net income over assets, share of deposits over assets, share of income from non-interest rate sources and share of equity over assets. All independent variables, including the banks' geographical footprint used to construct local characteristics, are lagged by 5 years from the year 2019 (except log assets) and standardized (except dfast). Observations are weighted by loans. T-statistics based on robust standard errors clustered at the HQ county-level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	IT Exp over Assets 1	IT Exp over Non-Interest Expense 2
Log Assets	0.0166***	0.677***
	(3.98)	(4.32)
Dfast	0.0279	0.907
	(0.85)	(0.79)
Fintech Exposure	0.0108**	0.369*
	(2.01)	(1.80)
Median Age	-0.00907**	-0.338**
	(-2.28)	(-2.24)
Branch Growth	-0.00559	-0.195
	(-1.52)	(-1.55)
STEM graduates	0.00167	0.109
	(0.26)	(0.49)
Math scores	0.00531	0.156
	(0.83)	(0.70)
HHI of deposits	-0.00441	-0.191
	(-1.14)	(-1.35)
Share of adults with tertiary education	0.00515 (0.86)	0.222 (1.03)
Income per capita	-0.0119**	-0.343*
	(-2.29)	(-1.74)
Population density	-0.00433*	-0.185*
	(-1.68)	(-1.84)
Broadband	0.00231	-0.0147
	(0.37)	(-0.06)
Share Minority	0.00368	0.107
	(1.04)	(0.80)
Loans / Assets	-0.00198	-0.0890
	(-0.29)	(-0.36)
Net income / Assets	-0.0132***	-0.468***
	(-3.17)	(-3.22)
Deposits / Assets	0.0132***	0.473***
	(2.96)	(2.97)
Net interest share of income	0.0183***	0.532***
	(5.02)	(3.82)
Equity / assets	-0.00356	-0.140
	(-0.69)	(-0.72)
Sample	All banks; 2019	All banks; 2019
R2	0.172	0.164
Observations	2,869	2,869
Mean	0.03	1.03
sd	0.07	2.3

TABLE 2

Determinants of banks' IT adoption with size interactions

Results of estimating the following cross-sectional equation: $IT_b = \alpha + \beta_L X_b \times Large_b + \beta_{SM} X_b \times (1 - Large_b) + \epsilon_b$ where b is a bank. IT_b are IT expenses normalized either by assets (1-2) or by non-interest expenses (3-4), averaged across 2015-2019. X_b is a set of bank-level controls including log value of assets, fintech exposure from 2010-2015, 5-year DHS growth of the number of branches with deposits from 2015-2019, county-level local characteristics such as the share of STEM among graduates and math scores of graduates from universities in the commuting zone, Herfindahl-Hirschman Index (HHI) of deposits, share of adults with tertiary education, income per capita, population density, share of population with access to broadband connection of at least 25 Mbps and share of minority population (non-white or Hispanic), and bank-level characteristics such as share of loans over assets, net income over assets, deposits over assets, income from non-interest rate sources and equity over assets. All independent variables, including the banks' geographical footprint used to construct local characteristics, are lagged by 5 years from the year 2019 (except log assets) and standardized. $Large_b$ 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 clustered at the HQ county-level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	IT Exp over Assets		IT Exp over Non-interest Expenses	
	1	2	3	4
Log Assets	0.0181***	0.0187***	0.743***	0.799***
	(3.12)	(2.76)	(3.37)	(3.07)
Small/medium × Fintech Exposure	0.00658**	0.00322	0.178*	0.0748
	(2.11)	(1.15)	(1.92)	(0.83)
Large × Fintech Exposure	0.0149*	0.0253**	0.548*	0.939**
	(1.87)	(2.20)	(1.78)	(2.13)
Small/medium × Median Age	-0.00245	-0.00265	-0.0696	-0.0947
	(-0.90)	(-1.16)	(-0.80)	(-1.12)
Large × Median Age	-0.00944**	-0.00962	-0.368**	-0.377*
	(-1.98)	(-1.60)	(-2.00)	(-1.65)
Small/medium × Income per Capita	0.000457	-0.000911	0.0327	-0.0350
	(0.17)	(-0.38)	(0.29)	(-0.37)
Large × Income per Capita	-0.0146**	-0.0225***	-0.432*	-0.674**
	(-2.48)	(-2.88)	(-1.88)	(-2.23)
Small/medium × Population Density	-0.000261	-0.00155	-0.0288	-0.0484
	(-0.19)	(-1.32)	(-0.53)	(-1.06)
Large × Population Density	-0.00276	0.000562	-0.136	-0.0383
	(-0.91)	(0.15)	(-1.13)	(-0.26)
Small/medium × Net Income / Assets	-0.00227	-0.00501***	-0.0784	-0.190***
	(-1.44)	(-2.77)	(-1.42)	(-2.74)
Large × Net Income / Assets	-0.00294	0.0000392	-0.191	-0.0951
	(-0.33)	(0.00)	(-0.59)	(-0.22)
Small/medium × Deposits / Assets	-0.00499**	-0.00204	-0.192**	-0.0972
	(-2.19)	(-0.80)	(-2.55)	(-1.01)
Large × Deposits / Assets	0.0133**	0.0178**	0.500*	0.693**
	(1.98)	(1.99)	(1.90)	(1.97)
Small/medium × Non-interest Share of Income	0.000453	0.00331	-0.0838	-0.0340
	(0.24)	(1.64)	(-1.31)	(-0.46)
Large × Non-interest Share of Income	0.0260***	0.0293***	0.677***	0.781***
	(5.01)	(4.88)	(3.37)	(3.36)
Definition of	Large = top 20%; 2019	Large = top 10%; 2019	Large = top 20%; 2019	Large = top 10%; 2019
R2	0.189	0.209	0.173	0.195
Observations	2869	2869	2869	2869
Test large vs small/medium: Fintech Exposure	0.294	0.049**	0.218	0.042**
Test large vs small/medium: Median Age	0.191	0.273	0.116	0.228
Test large vs small/medium: Income per Capita	0.021**	0.008***	0.081*	0.044**
Test large vs small/medium: Population Density	0.471	0.588	0.439	0.948
Test large vs small/medium: Net Income / Assets	0.940	0.677	0.730	0.829
Test large vs small/medium: Deposits / Assets	0.011**	0.033**	0.011**	0.028**
Test large vs small/medium: Non-interest Share of Income	0.000***	0.000***	0.000***	0.001***

TABLE 3

Determinants of banks' IT adoption, set of bivariate regressions

Table shows the β coefficient of various cross-sectional regressions of the form $IT_b = \alpha + \beta X_b + \delta \times \text{log assets} + \epsilon_b$ where b is a bank and X_b is a **univariate** bank-level variable whose name is listed in column (1) and described as in Table 1. IT_b are IT expenses normalized either by assets (Column 2) or by non-interest expenses (Column 3), averaged across 2015-2019. All independent variables, including the banks' geographical footprint used to construct local characteristics, are lagged by 5 years from the year 2019 (except log assets) and standardized. Observations are weighted by loans. T-statistics based on robust standard errors clustered at the HQ county-level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	IT Exp over Assets 1	IT Exp over Non-Interest Expense 2
Log Assets	0.0172**	0.674**
	(3.95)	(4.26)
Fintech Exposure	0.0128**	0.451**
	(2.31)	(2.16)
Median Age	-0.0115***	-0.428***
	(-2.89)	(-2.84)
Income per Capita	-0.00953***	-0.307***
	(-3.64)	(-2.97)
Population Density	-0.00687***	-0.243***
	(-4.72)	(-4.63)
Net income / Assets	-0.0113**	-0.413**
	(-2.11)	(-2.08)
Deposits /Assets	0.0132**	0.476**
	(2.43)	(2.47)
Non-interest share of income	0.0231***	0.697***
	(5.96)	(4.71)
Sample	All banks; 2019	All banks; 2019
Observations	2,869	2,869
Mean	0.03	1.03
sd	0.07	2.3

TABLE 4
IT adoption and fintech: IV estimation

Results of estimating the following two stage cross-sectional 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 2015-2019. X_b is a set of bank-level controls including log value of assets, 5-year DHS growth of the number of branches with deposits from 2015-2019, county-level local characteristics such as the share of STEM among graduates and math scores of graduates from universities in the commuting zone, Herfindahl-Hirschman Index (HHI) of deposits, share of adults with tertiary education, income per capita, population density, share of population with access to broadband connection of at least 25 Mbps and share of minority population (non-white or Hispanic), and bank-level characteristics such as share of loans over assets, net income over assets, deposits over assets, income from non-interest rate sources and equity over assets. $ExposureFintech_b$ is a measure of bank-level exposure to early (i.e. 2010-2015) fintech competition in the mortgage market. The instrument $Michigan_b$ is the share of deposits in the state of Michigan over the same years. All independent variables, including the banks' geographical footprint used to construct local characteristics, are lagged by 5 years from the year 2019 (except log assets, $Michigan_b$ and $ExposureFintech_b$) and standardized (except $Michigan_b$ and $ExposureFintech_b$). Observations are weighted by loans. Column (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.

	1	2	3	4	5	6	7	8	9
	Exposure to fintech	IT Exp over Assets				IT Exp over Non-Interest Expenses			
Exposure to fintech		0.580**		4.783*	6.328*	19.88*		139.0*	196.3*
		(2.01)		(1.77)	(1.92)	(1.80)		(1.82)	(1.88)
Michigan share of deposits	0.0118***		0.0566**				1.645**		
	(3.85)		(2.29)				(2.12)		
Log Assets	0.000624	0.0166***	0.0163***	0.0133***	0.0128**	0.675***	0.667***	0.580***	0.540***
	(1.21)	(3.98)	(3.98)	(2.78)	(2.48)	(4.32)	(4.32)	(3.56)	(3.03)
AR 10% CI:				[0.38, 10.44]	[0.74, 13.23]			[9.60, 293.87]	[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

TABLE 5

Log income + Minority (application level)

Results from estimating the regression $Y_{ilzt} = \beta\text{Class}_{lt} + \gamma X^1_{izt} + \zeta X^2_{lt-1} + \delta_{zt} + \epsilon_{ilzt}$ 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. Mortgage originated between 2018 and 2021 are included. All standard errors are clustered at the lender level. Number of banks range from 2893 in 2018 to 1907 in 2021.

	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

TABLE 6

Acceptance rate of different lenders

Results from estimating the panel regression
$\text{Accept}_{ilzt} = \beta \text{Class}_{lt} + \text{Class}_{lt} \times \text{minority}_{ilzt} + \text{Class}_{lt} \times \text{income}_{ilzt} + \gamma X^1_{izt} + \zeta X^2_{lt-1} + \delta_{zt} + \epsilon_{ilzt}$ 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. Mortgage originated between 2018 and 2021 are included. All standard errors are clustered at the lender level. Number of banks range from 2893 in 2018 to 1907 in 2021.

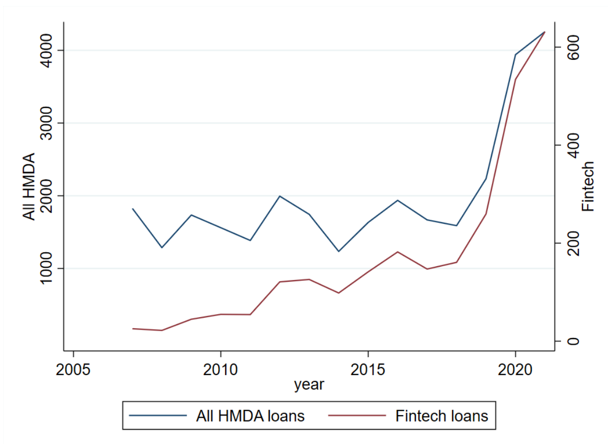
	1	2	3
High IT	-0.06	-0.06	0.17
	(0.04)	(0.05)	(0.11)
Fintech	0.04	0.23***	0.39***
	(0.06)	(0.06)	(0.12)
Non Banks	0.01	0.08	0.32***
	(0.04)	(0.06)	(0.11)
Minority=1 × Low IT			0.01
			(0.01)
Minority=1 × High IT			-0.01
			(0.01)
Minority=1 × Fintech			0.01***
			(0.00)
Minority=1 × Non Banks			0.01***
			(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

A. Internet Appendix

FIGURE A1
Mortgage markets and fintech shares

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

Graph A. Total mortgage value in Bn$



Graph B. Fintech share

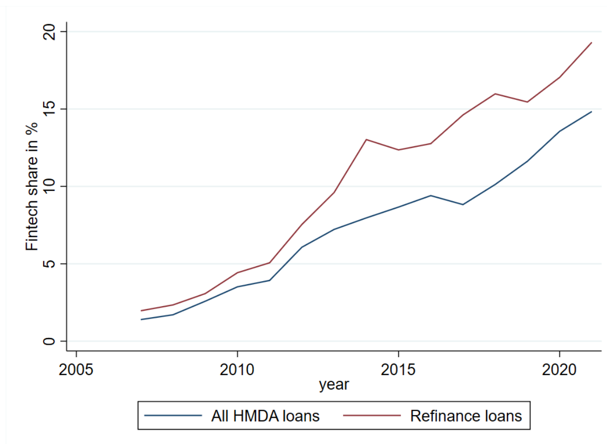
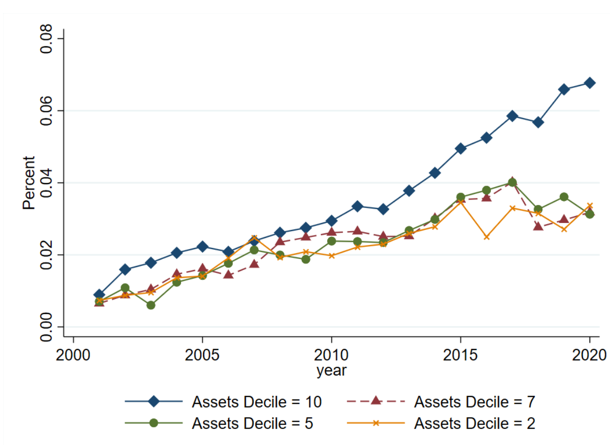


FIGURE A2
IT expenses over time by bank size for those with some listed non-interest expenses

The figure shows the average (non-weighted) IT expenses over assets (Graph A) or over non-interest expenses (Graph B) for US banks according to bank size (decile of assets). We include only those US banks that listed some non-interest expenses in the descriptive category of Call reports.

Graph A. Normalized by assets



Graph B. Normalized by non-interest expenses

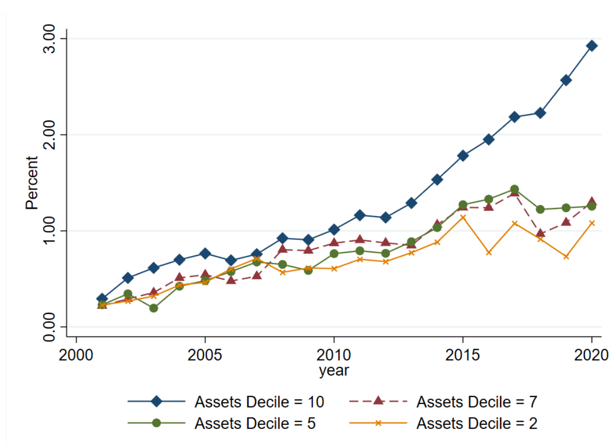
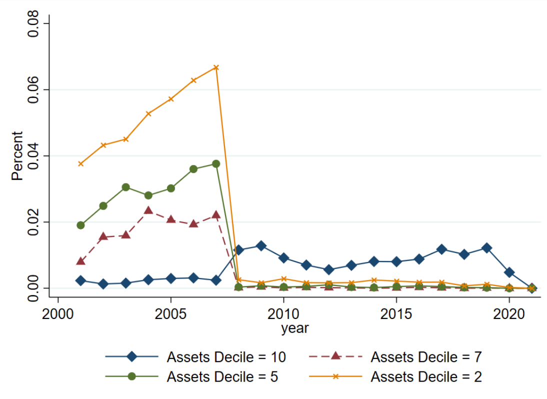


FIGURE A3

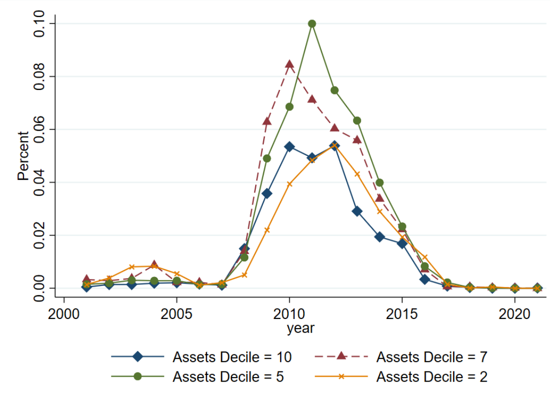
Other non IT non-interest over time by bank size - part 1

This is part 1 of a figure which shows the evolution of different non-interest expenses over time, normalized by assets, by bank-size category. The keywords chosen to construct data from the descriptive category of non-interest expenses in the call reports for graphs A-H are "audit", "oreo", "insurance", "management", "atm", "training", "travel", and "correspondence" respectively.

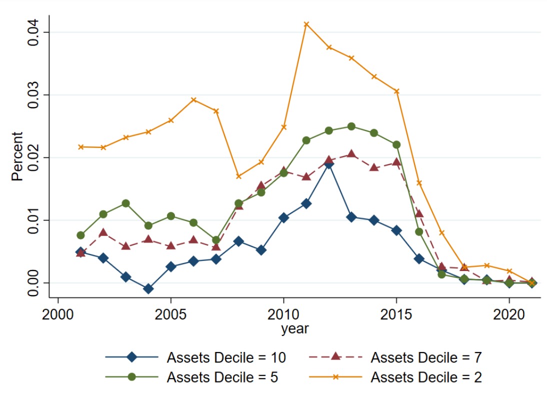
Graph A. Audit



Graph B. Other Real Estate Owned



Graph C. Insurance



Graph D. Management

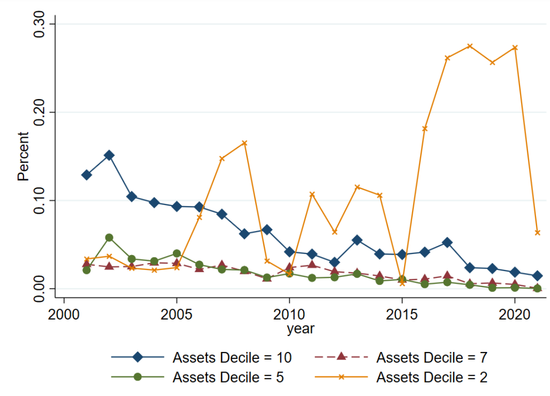
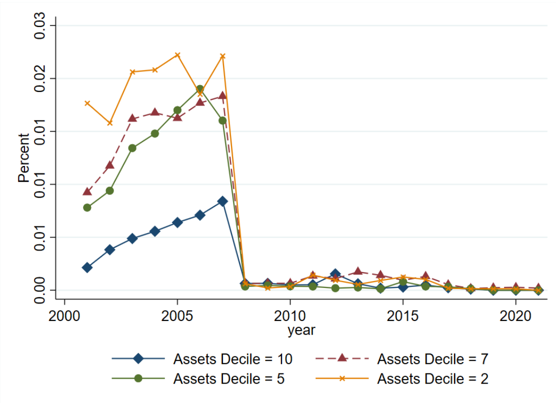


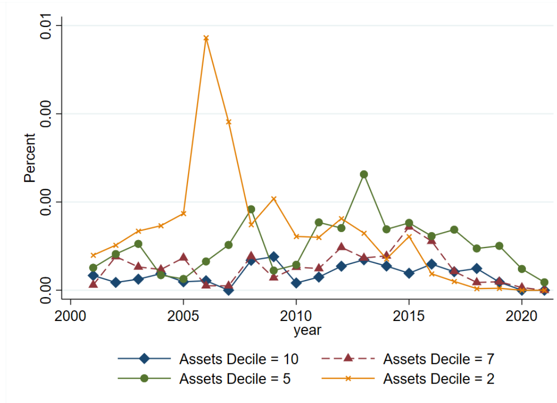
FIGURE A4
Other non IT non-interest over time by bank size - part 2

This is part 2 of a figure which shows the evolution of different non-interest expenses over time, normalized by assets, by bank-size category. The keywords chosen to construct data from the descriptive category of non-interest expenses in the Call reports for graphs A-H are “audit”, “oreo”, “insurance”, “management”, “atm”, “training”, “travel”, and “correspondence”, respectively.

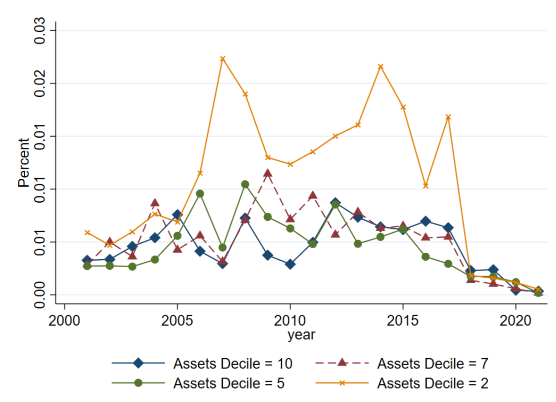
Graph E. ATM



Graph F. Training



Graph G. Travel



Graph H. Correspondence

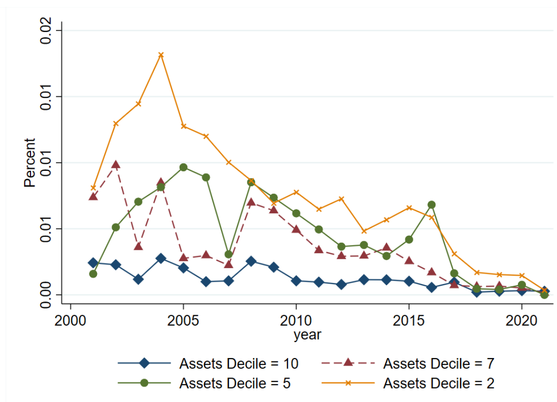


FIGURE A5

Capital IQ Technology Expenses over time

The figure shows average Capital IQ technology expenses over assets for the years 2015-2019 (Panel a) with a total of 2511 observations. The panel includes bank-level observations for which Capital IQ records could be matched to Call Reports data using `bhcid`, and for which total assets differ by less than 3 percent from those reported in Capital IQ Pro.

Capital IQ Technology Expenses over Assets in Percent

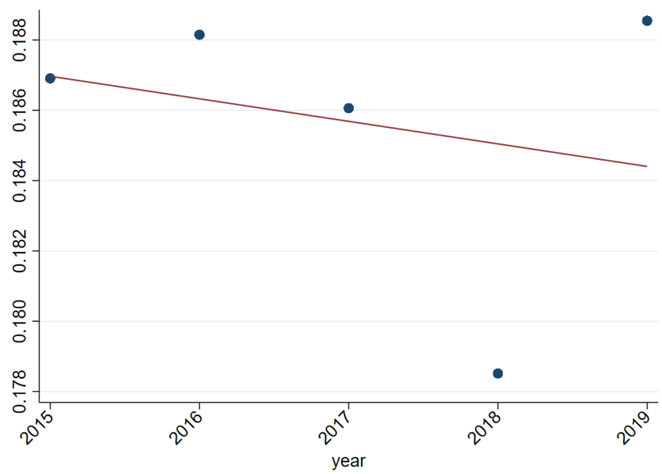
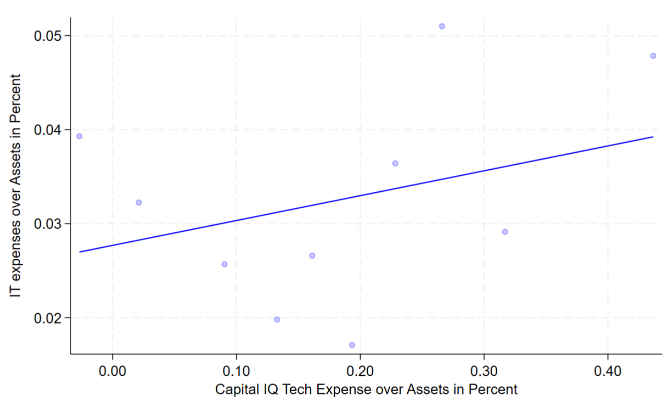


FIGURE A6

Comparison with Capital IQ Technology Expenses

The figure shows binscatter plots of Capital IQ technology expenses over assets against our IT expenses over assets measure (Graph A) and Aberdeen IT budget over assets (Graph B), all in percent, winsorized at 1% and controlling for the log of assets of the bank for the year 2019. Note: the sample includes 412 banks that were present in all the three datasets: Capital IQ, Aberdeen and Call Reports. The sample is the 2019 cross-section of 412 bank–level observations for which CAP IQ records could be matched to Call Reports or Aberdeen data on `bhcid` and whose total-asset figures differ by less than 3 percent to those observed in Capital IQ Pro.

Graph A. IT Expenses over Assets in Percent



Graph B. Aberdeen IT Budget over Assets in Percent

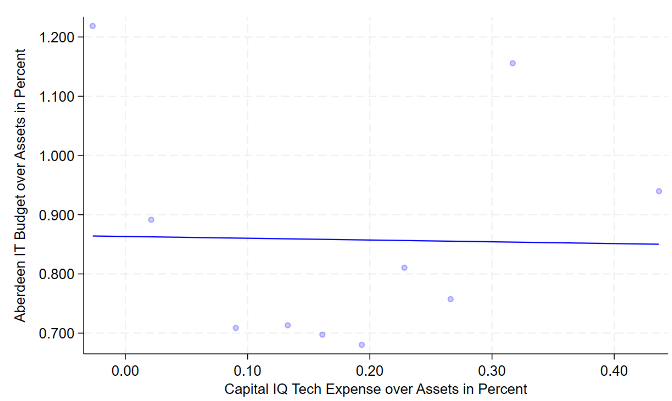
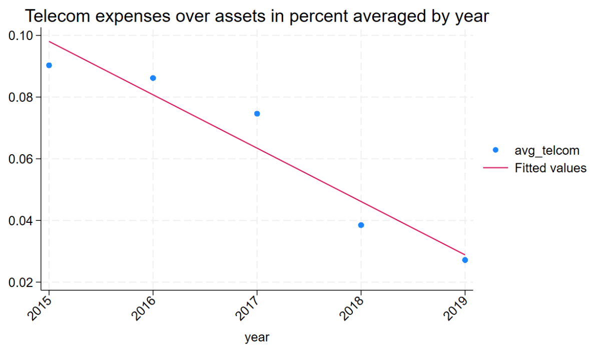


FIGURE A7

Telecommunications and data processing expenses by year

Graphs A and B plot the average of telecommunication expenses over assets and data processing expenses over assets by year, respectively. These expenses are reported in the series “RIADF559” and “RIADC017”, respectively, in the Call reports. The sample of banks is the banks common between Call Reports and Capital IQ.

Graph A. Telecommunications over assets



Graph B. Data processing over assets

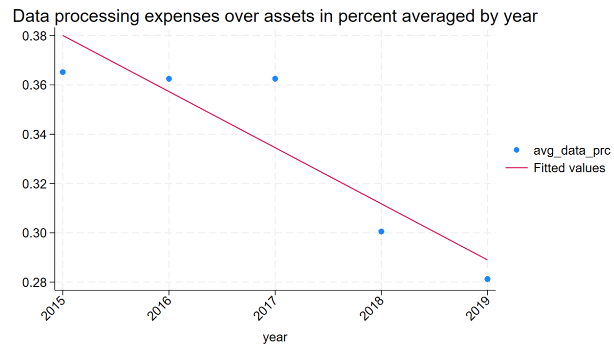
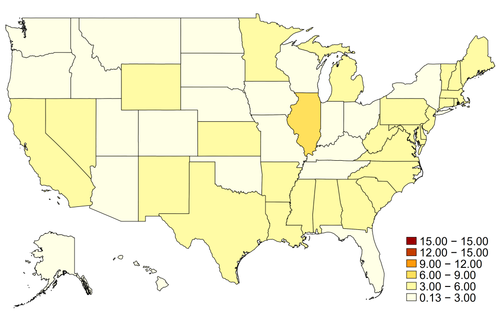


FIGURE A8

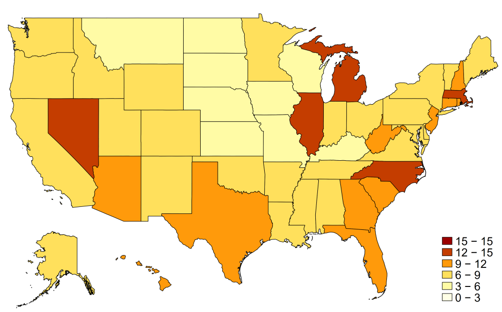
Fintech share in different states

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.

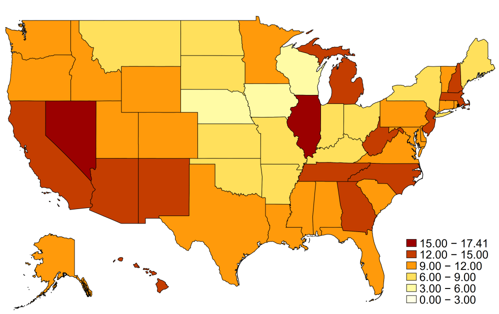
Graph A. 2010



Graph B. 2015



Graph C. 2019



Graph D. 2021

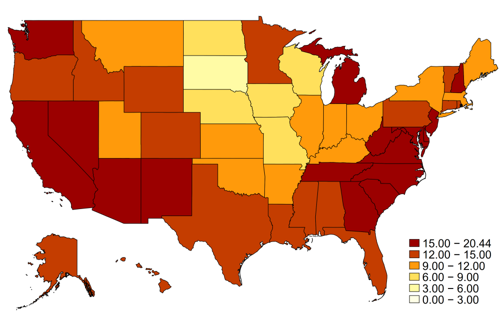
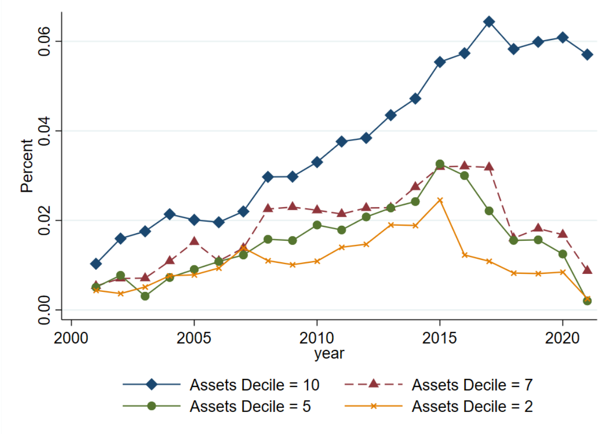


FIGURE A9

IT expenses over time by bank size–balanced panel

This figure shows the average (non-weighted) IT expenses over assets (Graph A) or over non-interest expenses (Graph 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.

Graph A. Normalized by assets



Graph B. Normalized by non-interest expenses

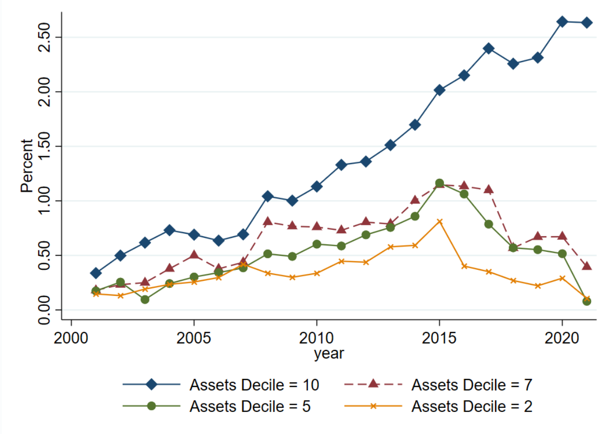
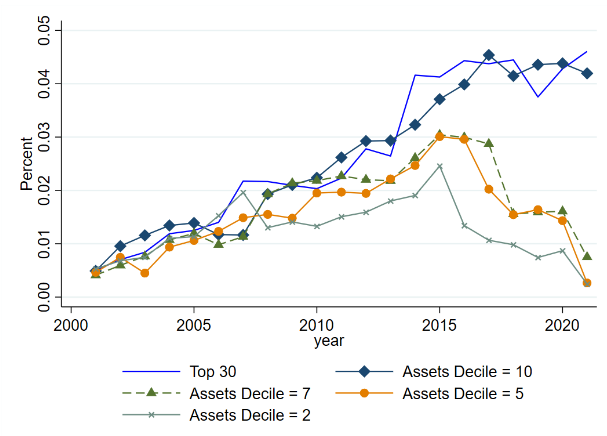


FIGURE A10

IT expenses over time by bank size–isolating top 30

This figure shows the average (non-weighted) IT expenses over assets (Graph A) or over non-interest expenses (Graph 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.

Graph A. Normalized by assets



Graph B. Normalized by non-interest expenses

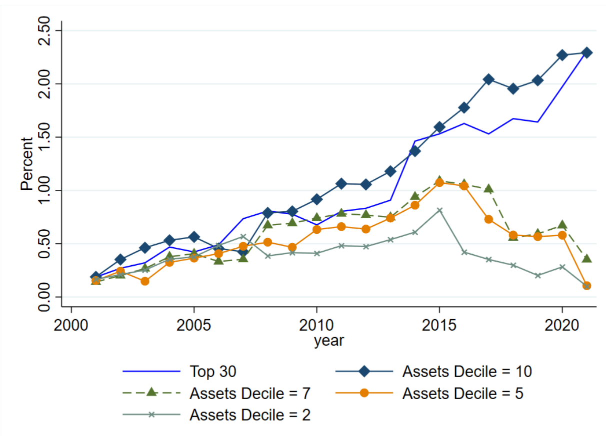


FIGURE A11

IT expenses over time by bank size including top 1%

This figure shows the average (non-weighted) IT expenses over assets (Graph A) or over non-interest expenses (Graph B) for US banks according to bank size (decile of assets as well as the top 1%) .

Graph A. Normalized by assets **Graph B. Normalized by non-interest expenses**

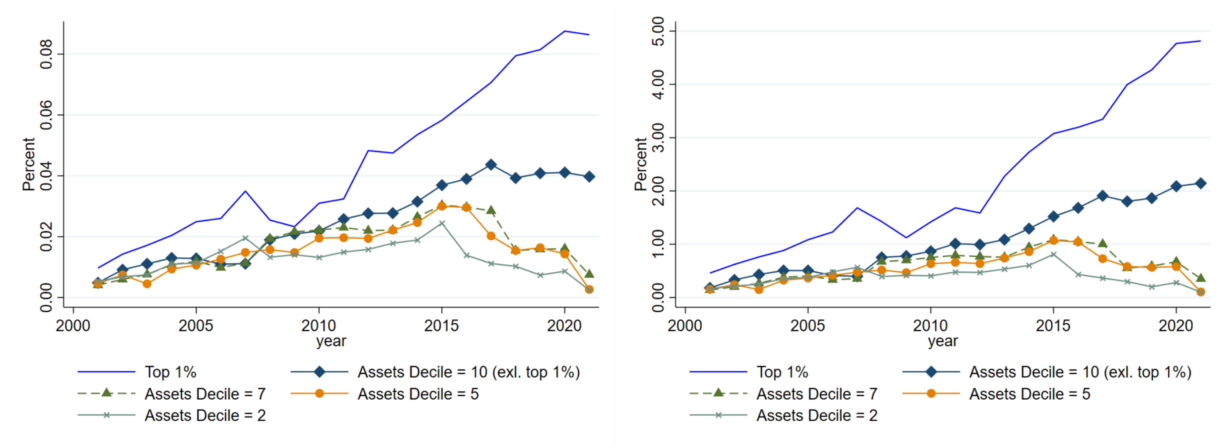


FIGURE A12

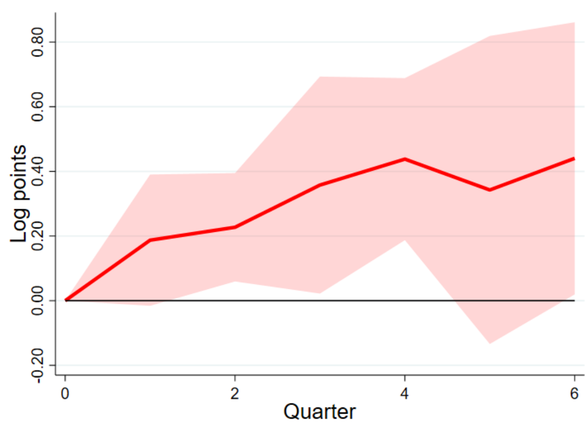
Bank loans' response to monetary policy: IT heterogeneity with IT normalized by assets

Graphs A and B plot the estimated interaction coefficients α^h. from the panel data local-projection

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

where $Y_{b,t}$ denotes bank b's loans (Graph A) or interest income on loans over loans (Graph B) in quarter t, and $\Delta^h \log Y_{b,t} = \log Y_{b,t+h} - \log Y_{b,t-1}$. MP_{t-1} is a monetary policy shock from Jarociński and Karadi (2020); $IT_{b,y(t-4)}$ is the bank's average IT expenditure over the previous five years, normalized by assets. δ_b and ζ_t denote bank and quarter fixed effects, and $X_{b,t}$ is a vector of time-varying controls which includes lagged (by on year) time-varying bank variables such as equity, deposits, net income, loans normalized by assets, share of non-interest income, and log of assets. Shaded areas indicate 90% and 95% confidence intervals. Time period is from 2002Q1 (8K banks) to 2019Q3 (5K banks).

Graph A. Loans: Interaction term



Graph B. Interest Rate Earned on Loans: Interaction term

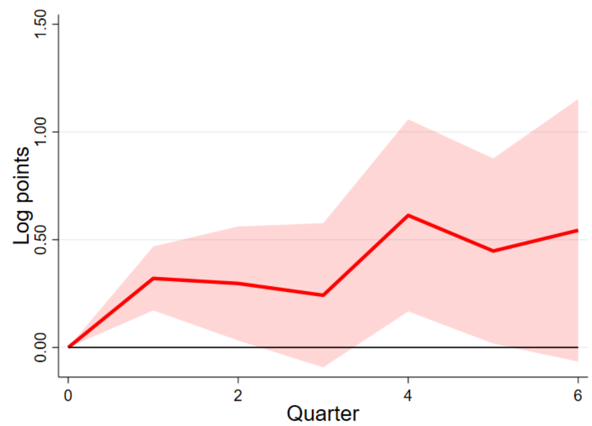


FIGURE A13

Graphical Illustration of the impact of MP tightening

This figure shows how a monetary tightening—modeled as an upward shift in the bank funding supply curve—affects banks with different IT. High IT banks face less elastic residual demand (steeper demand), allowing them to pass through more of the funding cost increase via higher rates and suffer smaller quantity declines. Low IT banks face more elastic demand, leading to larger quantity reductions and smaller rate increases.

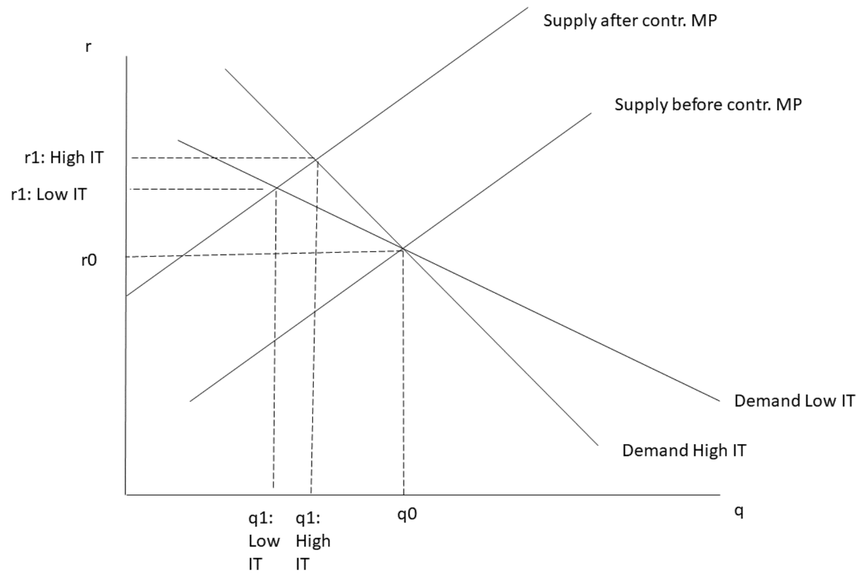


FIGURE A14

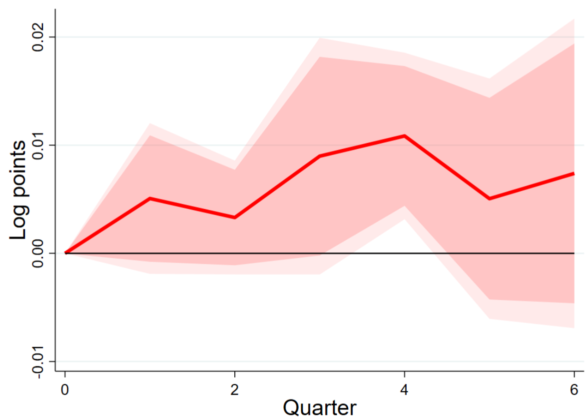
Bank loans' response to monetary policy: IT heterogeneity with additional interacted controls

Graphs A and B plot the estimated interaction coefficients α^h. from the panel data local-projection

$$\Delta^h \log Y_{b,t} = \delta_b + \zeta_t + \alpha^h MP_{t-1} \times IT_{b,y(t-4)} + \gamma X_{b,t} + \chi MP_{t-1} \times X_{b,t} + \varepsilon_{b,t},$$

where $Y_{b,t}$ denotes bank b's loans (Graph A) or interest income on loans over loans (Graph B) in quarter t, and $\Delta^h \log Y_{b,t} = \log Y_{b,t+h} - \log Y_{b,t-1}$. MP_{t-1} is a monetary policy shock from Jarociński and Karadi (2020); $IT_{b,y(t-4)}$ is the bank's average IT expenditure over the previous five years, normalized by non-interest expenses. δ_b and ζ_t denote bank and quarter fixed effects, and $X_{b,t}$ is a vector of time-varying controls which includes lagged (by on year) time-varying bank variables such as equity, deposits, net income, loans normalized by assets, share of non-interest income, and log of assets. Observations are weighted by loans. Standard errors are double-clustered at the bank and quarter levels. Shaded areas indicate 90% and 95% confidence intervals. Time period is from 2002Q1 (8K banks) to 2019Q3 (5K banks).

Graph A. Loans: Interaction term



Graph B. Interest Rate Earned on Loans Interaction term

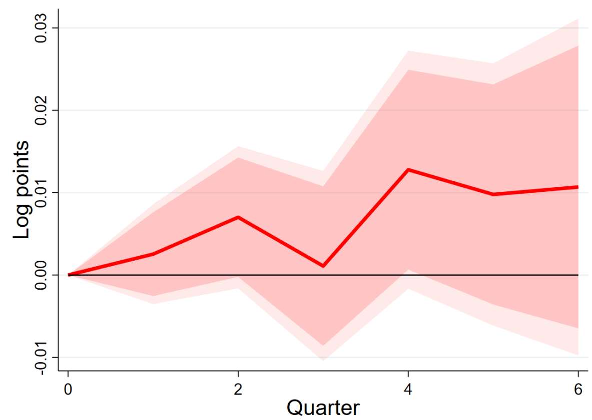


TABLE A1

Determinants of banks' IT adoption using Capital IQ data

Results of estimating the following cross-sectional equation: $IT_b = \alpha + \beta X_b + \epsilon_b$, where b is a bank. IT_b are Call report IT expenses normalized either by assets (1) or by non-interest expenses (2), Capital IQ Tech expenses normalized either by assets (3) or by non-interest expenses (4), averaged across 2015–2019. X_b is a set of bank-level controls including log value of assets, dfast (a dummy equal to one if the bank participated in a Dodd-Frank Act stress test), fintech exposure from 2010–2015, 5-year growth of the number of branches with deposits from 2015–2019, county-level local characteristics such as the median age, share of STEM among graduates from universities in the commuting zone, math scores of graduates from universities in the commuting zone, Herfindahl-Hirschman Index (HHI) of deposits, share of adults with tertiary education, income per capita, population density, share of population with access to broadband connection of at least 25 Mbps and share of minority population (non-white or Hispanic), and bank-level characteristics such as share of loans over assets, share of net income over assets, share of deposits over assets, share of income from non-interest rate sources and share of equity over assets. All independent variables, including the banks' geographical footprint used to construct local characteristics, are lagged by 5 years from the year 2019 (except log assets) and standardized (except dfast). Observations are weighted by loans. T-statistics based on robust standard errors clustered at the HQ county-level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	IT expenses over		Cap IQ IT expenses over	
	Assets	Non-Interest Expenses	Assets	Non-interest expenses
	1	2	3	4
Log Assets	0.0166***	0.677***	-0.0223***	-0.461
	(3.98)	(4.32)	(-3.01)	(-1.53)
Dfast	0.0279	0.907	-0.0190	-1.489
	(0.85)	(0.79)	(-0.28)	(-0.67)
Fintech Exposure	0.0108**	0.369*	0.0104	0.0683
	(2.01)	(1.80)	(1.07)	(0.22)
Median Age	-0.00907**	-0.338**	0.0113	0.263
	(-2.28)	(-2.24)	(1.27)	(0.75)
Branch Growth	-0.00559	-0.195	-0.00433	-0.169
	(-1.52)	(-1.55)	(-0.86)	(-0.83)
STEM graduates	0.00167	0.109	-0.0188*	-0.811**
	(0.26)	(0.49)	(-1.89)	(-2.29)
Math scores	0.00531	0.156	0.0315***	1.109***
	(0.83)	(0.70)	(3.13)	(3.04)
HHI of deposits	-0.00441	-0.191	-0.00810	-0.418
	(-1.14)	(-1.35)	(-0.84)	(-1.11)
Share of adults with tertiary education	0.00515	0.222	0.0108	0.326
	(0.86)	(1.03)	(0.79)	(0.59)
Income per capita	-0.0119**	-0.343*	-0.0327***	-0.781
	(-2.29)	(-1.74)	(-3.08)	(-1.64)
Population density	-0.00433*	-0.185*	0.00860	0.283
	(-1.68)	(-1.84)	(0.93)	(0.56)
Broadband	0.00231	-0.0147	-0.00715	-0.535*
	(0.37)	(-0.06)	(-0.95)	(-1.67)
Share Minority	0.00368	0.107	0.00421	0.132
	(1.04)	(0.80)	(0.63)	(0.49)
Loans / Assets	-0.00198	-0.0890	-0.00223	-0.0698
	(-0.29)	(-0.36)	(-0.25)	(-0.19)
Net income / Assets	-0.0132***	-0.468***	-0.00646	-0.169
	(-3.17)	(-3.22)	(-0.62)	(-0.41)
Deposits / Assets	0.0132***	0.473***	0.0104	-0.0385
	(2.96)	(2.97)	(1.19)	(-0.13)
Net interest share of income	0.0183***	0.532***	0.0209***	-0.260
	(5.02)	(3.82)	(2.83)	(-0.75)
Equity / Assets	-0.00356	-0.140	-0.00613	0.0134
	(-0.69)	(-0.72)	(-0.52)	(0.03)
Sample	All banks; 2019	All banks; 2019	All banks; 2019	All banks; 2019
R2	0.172	0.164	0.157	0.0951
Observations	2869	2869	559	559
Mean	.03	1.03	.19	6.7
sd	.07	2.33	.13	3.95

TABLE A2

Summary statistics for the independent variables in Table 1

This table presents the descriptive statistics for the variables employed in the cross sectional analysis of the drivers of IT investments, those results are presented in Table 1. The sample includes slightly less than 3,000 banks out of the 5,000 in the 2019 Call report. We include only banks that we can merge across Call reports, FDIC, and HMDA datasets for the period 2015-2019.

	Mean	N	Sd	Min	Max
Log assets (in 000s, USD)	13.06	2872	1.40	9.88	17.93
Fintech exposure (share)	0.06	2872	0.02	0.01	0.18
DHS Branch growth	0.12	2872	0.31	-1.69	1.94
STEM graduates (share)	0.38	2872	0.13	0.04	1.00
Math score (SAT)	617.62	2872	47.33	445.53	780.00
HHI of deposits	1983.19	2872	1089.98	548.54	9684.28
Education (share)	0.27	2872	0.07	0.10	0.48
Income per capita (in 000s,USD)	25.31	2872	8.81	6.92	89.59
Population density (per square km)	1355.74	2872	5103.47	1.33	69357.68
Broadband (percent)	27.61	2872	16.70	0.00	70.00
Share minority (percent)	14.72	2872	19.19	0.00	85.65
Loans/Assets (percent)	64.24	2872	14.95	0.00	88.57
Net income/Assets (share)	0.83	2872	0.68	-1.90	6.50
Deposits/Assets (percent)	13.74	2872	9.09	0.00	39.14
Share of non interest income (percent)	64.47	2872	34.28	0.00	100.00
Equity/Assets (percent)	11.25	2872	3.48	2.00	39.60

TABLE A3

Determinants of banks' IT adoption, Poisson regression

Results of estimating the following cross-sectional Poisson regression through log likelihood: $IT_b = \alpha + \beta X_b + \epsilon_b$ where b is a bank. IT_b are IT expenses normalized either by assets (1) or by non-interest expenses (2), averaged across 2015-2019. X_b is a set of bank-level controls including log value of assets, dfast (a dummy equal to one if the bank participated in a Dodd-Frank Act stress test), fintech exposure from 2010-2015, 5-year DHS growth of the number of branches with deposits from 2015-2019, county-level local characteristics such as the median age, share of STEM among graduates from universities in the commuting zone, math scores of graduates from universities in the commuting zone, Herfindahl-Hirschman Index (HHI) of deposits, share of adults with tertiary education, income per capita, population density, share of population with access to broadband connection of at least 25 Mbps and share of minority population (non-white or Hispanic), and bank-level characteristics such as share of loans over assets, share of net income over assets, share of deposits over assets, share of income from non-interest rate sources and share of equity over assets. All independent variables, including the banks' geographical footprint used to construct local characteristics, are lagged by 5 years from the year 2019 (except log assets) and standardized (except dfast). Observations are weighted by loans. T-statistics based on robust standard errors clustered at the HQ county-level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	IT Exp over Assets 1	IT Exp over Non-Interest Expense 2
Log Assets	0.385*** (5.42)	0.416*** (5.80)
Dfast	0.227 (0.69)	0.187 (0.59)
Fintech Exposure	0.315** (2.54)	0.293** (2.31)
Median Age	-0.217*** (-2.62)	-0.222*** (-2.61)
Branch Density	-0.103 (-1.47)	-0.0954 (-1.52)
STEM graduates	0.0968 (0.91)	0.113 (1.11)
Math scores	0.0655 (0.51)	0.0406 (0.32)
HHI of deposits	-0.0795 (-0.90)	-0.109 (-1.22)
Share of adults with tertiary education	0.129 (0.94)	0.145 (1.06)
Income per capita	-0.280** (-2.32)	-0.213* (-1.78)
Population density	-0.193** (-2.13)	-0.188** (-2.20)
Broadband	0.102 (0.93)	0.0428 (0.38)
Share White	0.0943 (1.39)	0.0782 (1.17)
Loans / Assets	-0.0264 (-0.26)	-0.0278 (-0.28)
Net income / Assets	-0.386*** (-3.12)	-0.365*** (-3.60)
Deposits / Assets	0.252*** (3.85)	0.239*** (3.47)
Net interest share of income	0.445*** (4.82)	0.328*** (3.61)
Equity / assets	-0.0964 (-1.00)	-0.0955 (-1.00)
Sample	All banks; 2019	All banks; 2019
Log pseudolikelihood	-4.948e+08	-7.342e+09
Mean	0.03	1.03
sd	0.07	2.3

TABLE A4

Determinants of banks' IT adoption: Role of Dodd-Frank stress test

Results of estimating the following panel regression at the bank-year level: $IT_{bt} = \alpha + \beta * dfast_{bt} + X_{bt} + \epsilon_{bt}$ where b is a bank. IT_b are IT expenses normalized either by assets (1) or by non-interest expenses (2), $dfast_{bt}$ (a dummy equal to one if the bank participated in a Dodd-Frank Act stress test in a given year), X_{bt} is a set of bank-level controls (standardized) including log value of assets, share of loans over assets, share of net income over assets, share of deposits over assets, share of income from non-interest rate sources and share of equity over assets. Observations between 2009 and 2021 are included. There are around 6500 banks in the sample in 2009 and around 4600 banks in 2021. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	IT Expenses over Assets				IT Expenses over Non-Interest Expenses			
	1	2	3	4	5	6	7	8
year_dfast	0.0243	0.0146**	0.0145**	0.00621	0.886	0.649**	0.628**	0.295
	(1.53)	(2.47)	(2.44)	(1.10)	(1.46)	(2.34)	(2.30)	(1.23)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Controls	No	No	Yes	Yes	No	No	Yes	Yes
Year FE $\times$ Size	No	No	No	Yes	No	No	No	Yes
R2	0.00784	0.652	0.652	0.655	0.00703	0.655	0.655	0.660
Observations	69851	69819	69819	69819	69779	69741	69741	69741
Mean	0.02	0.02	0.02	0.02	0.75	0.75	0.75	0.75
SD	0.062	0.062	0.062	0.062	2.15	2.15	2.15	2.15

TABLE A5

IT adoption and Mortgage reliance

Results of estimating the following cross-sectional regression:

$$
\begin{aligned}
IT_b = {} & \alpha + \beta Michigan_b + \gamma Mortgage_b + \chi Michigan_b \times Mortgage_b \\
& + \phi Michigan_b \times LogAssets_b + \psi LogAssets_b \times Mortgage_b \\
& + \omega Michigan_b \times LogAssets_b \times Mortgage_b + \xi X_b + \varepsilon_b
\end{aligned}
$$

where b is a bank. IT_b are IT expenses normalized either by assets (1) or by non-interest expenses (2), averaged across 2015-2019. X_b is a set of bank-level controls including log value of assets (standardized), 5-year DHS growth of the number of branches with deposits, county-level local characteristics such as the share of STEM among graduates and math scores of graduates from universities in the commuting zone, Herfindahl-Hirschman Index (HHI) of deposits, share of adults with tertiary education, income per capita, population density, share of population with access to broadband connection of at least 25 Mbps and share of minority population (non-white or Hispanic), and bank-level characteristics such as share of loans over assets, net income over assets, deposits over assets, income from non-interest rate sources and equity over assets. The instrument $Michigan_b$ is the share of deposits in the state of Michigan over the same years i.e., 2015-2019. $Mortgage_b$ is standardized and defined as the total HMDA loan origination value divided by assets. All independent variables, including the banks' geographical footprint used to construct local characteristics, are lagged by 5 years from the year 2019 except for $Michigan_b$. Observations are weighted by loans. T-statistics based on robust standard errors clustered at the HQ county-level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	IT expenses over Assets	IT expenses over Non-Interest Expenses
	1	2
Michigan	-0.0615**	-1.879**
	(-2.54)	(-2.24)
Mortgage reliance	0.0115*	0.356
	(1.67)	(1.56)
Michigan × Mortgage reliance	0.00859	0.128
	(0.48)	(0.26)
Log assets	0.0185***	0.743***
	(4.04)	(4.29)
Michigan × Log assets	0.105***	3.416***
	(3.34)	(3.15)
Log assets × Mortgage reliance	-0.0227**	-0.958***
	(-2.24)	(-2.86)
Michigan × Log assets × Mortgage reliance	0.00291	0.260
	(0.20)	(0.54)
Specification	Reduced Form	Reduced Form
R2	0.194	0.184
Observations	2746	2746

TABLE A6
IT expenses and Michigan exposure: placebo test

Results of estimating the cross-sectional equation:

$$IT_b = \alpha + \beta Michigan_b + \gamma OtherState_b + \xi \log(assets) + \epsilon_b$$

where b is a bank. IT_b are IT expenses normalized either by assets (1-2) or by non-interest expenses (3-4), averaged across 2015-2019. $Michigan_b$ is the average share of bank b's deposits in Michigan branches, averaged 2010-2015. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	1	2	3	4
	IT Exp over Assets		IT Exp over Non-Interest Expenses	
Michigan share of deposits	0.0809***	0.0722**	2.529**	2.271**
	(2.59)	(2.31)	(2.32)	(2.05)
Indiana share of deposits	-0.0314	-0.0296	-1.303	-1.251
	(-1.07)	(-1.00)	(-1.28)	(-1.22)
Ohio share of deposits	-0.00653	-0.00578	0.151	0.174
	(-0.33)	(-0.28)	(0.16)	(0.18)
Wisconsin share of deposits	-0.0180	-0.0185	-0.678	-0.694
	(-1.20)	(-1.21)	(-1.21)	(-1.23)
Minnesota share of deposits		0.0303		0.931
		(0.85)		(0.77)
Illinois share of deposits		0.0201		0.566
		(1.39)		(1.03)
log Assets	0.0119***	0.0121***	0.469***	0.476***
	(3.84)	(3.92)	(4.17)	(4.23)
R2	0.0585	0.0607	0.0655	0.0670
Observations	2848	2848	2848	2848

TABLE A7
Bank loans' response to monetary policy: IT heterogeneity

Table shows the estimated interaction coefficients α^h. from the panel data local-projection

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

where $Y_{b,t}$ denotes bank b's loans in quarter t, and $\Delta^h \log Y_{b,t} = \log Y_{b,t+h} - \log Y_{b,t-1}$. MP_{t-1} is a monetary policy shock from Jarociński and Karadi (2020); $IT_{b,y(t-4)}$ is the bank's average IT expenditure over the previous five years, normalized by non-interest expenses. δ_b and ζ_t denote bank and quarter fixed effects, and $X_{b,t}$ is a vector of time-varying controls which includes lagged (by on year) time-varying bank variables such as equity, deposits, net income, loans normalized by assets, share of non-interest income, and log of assets. Observations are weighted by loans. Standard errors are double-clustered at the bank and quarter levels. Time period is from 2002Q1 (8K banks) to 2019Q3 (5K banks). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	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

TABLE A8

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

Table shows the estimated interaction coefficients α^h. from the panel data local-projection

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

where $Y_{b,t}$ denotes bank b's interest income on loans over loans in quarter t, and $\Delta^h \log Y_{b,t} = \log Y_{b,t+h} - \log Y_{b,t-1}$. MP_{t-1} is a monetary policy shock from Jarociński and Karadi (2020); $IT_{b,y(t-4)}$ is the bank's average IT expenditure over the previous five years, normalized by non-interest expenses. δ_b and ζ_t denote bank and quarter fixed effects, and $X_{b,t}$ is a vector of time-varying controls which includes lagged (by on year) time-varying bank variables such as equity, deposits, net income, loans normalized by assets, share of non-interest income, and log of assets. Observations are weighted by loans. Standard errors are double-clustered at the bank and quarter levels. Time period is from 2002Q1 (8K banks) to 2019Q3 (5K banks). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	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