The Importance of Technology in Banking during a Crisis *

Nicola Pierri † Yannick Timmer‡

Forthcoming in the *Journal of Monetary Economics*

Abstract

What are the implications of information technology (IT) in banking for financial stability? Data on US banks' IT equipment and the background of their executives reveals that higher pre-crisis IT adoption led to fewer non-performing loans and more lending during the global financial crisis. Empirical evidence indicates a direct role of IT adoption in strengthening bank resilience; this includes instrumental variable estimates exploiting the historical location of technical schools. Loan-level analysis shows that high-IT banks originated mortgages with better performance, indicating better borrower screening. No evidence points to offloading of low-quality loans, differences in business models, or enhanced monitoring.

JEL Codes: O3, G21, G14, E44, D82, D83

Keywords: Technology, Financial Stability, IT Adoption, Non-Performing Loans, Screening

*This paper is a revised version of the IMF WP 20/14 with title "Tech in Fin before FinTech: Blessing or Curse for Financial Stability?". We are grateful to Urban Jermann (editor), Joseph Vavra (the associated editor), and an anynomous referee for invaluable feedback that significantly improved the paper during the revision process. We thank Tobias Adrian, Andrea Ajello, David Aikman (discussant), Ufuk Akcigit, Tobias Berg, Barbara Biasi, Markus Brunnermeier, Hans Degryse (discussant), Giovanni Dell'Ariccia, Enrica Detragiache, Douglas Diamond, Ehsan Ebrahimy, Andreas Fuster (discussant), Ann Harrison, Peter Hoffmann, Deniz Igan, Divya Kirti, Simone Lenzu, Davide Malacrino, Atif Mian, Sole Martinez Peria, Cyril Pouvelle (discussant), Andrea Presbitero, Damien Puy, Lev Ratnovski, Gustavo Suarez, Suchanan Tambunlertchai, James Vickery (discussant), Gregor Weiss, Torsten Wezel, Brian Wolfe (discussant), and seminar and conference participants at Third Bergen FinTech conference 2020, EBA Policy Research Workshop, BIS/BoE/CEPR Conference on Financial Innovation: Implications for Competition, Regulation and Monetary Policy, EFA, IWH-FIN-FIRE Workshop on Challenges to Financial Stability, CAFR Workshop on Fintech, Cass Business School, ECB, Fed, IMF, Villanova University, and RESMF annual conference for their insightful comments. Nicola Pierri is grateful to Nick Bloom for guidance and support during the early stages of the project. We thank Chenxu Fu, Hala Moussawi, and Huy Nguyen for excellent research assistance and Gladys Cheng and Sylvie Poirot for help with data sources. All remaining errors are our sole responsibility. The views expressed in the paper are those of the authors and do not necessarily represent the views of the IMF, its Executive Board, or its Management nor of the Federal Reserve Board or the Federal Reserve System.

†International Monetary Fund. 1900 Pennsylvania Avenue NW, Washington DC. Email: npierri@imf.org

‡Federal Reserve Board. Email: yannick.timmer@frb.gov

1 Introduction

Banks' massive investments in Information Technology (IT), and the more recent worldwide emergence of FinTech, have generated a debate on the financial stability impact of IT (Claessens et al., 2018; FSB, 2019; Carletti et al., 2020; Boot et al., 2021). FinTech and the latest technological developments have been changing the way information is processed and the relative consequences for credit allocation and performance (Berg et al., 2019; Di Maggio and Yao, 2021; Fuster et al., 2019, e.g). However, a paramount question that remains largely unaddressed is whether IT adoption affects banks' resilience during periods of financial stress.

To understand the potential impact of higher technology intensity in lending on financial stability, we study the non-performing loans on the balance sheet of US banks with a heterogeneous degree of IT adoption during the Global Financial Crisis (GFC). The sign of the relationship between IT adoption and non-performing loans is a-priori ambiguous. Advances in technology can improve monitoring and screening thanks to the enhanced ability to collect, store, communicate, and process information (Liberti and Petersen, 2018). However, banks with more IT adoption might rely too much on "hard" information, which are easier to report and communicate, inducing them to neglect "soft" information (Rajan, 2006; Rajan et al., 2015).

We find that US commercial banks which were leaders in IT adoption before the GFC were significantly more resilient during the crisis. Figure 1 illustrates this striking pattern: high- and low-IT adoption banks had the same level of NPL over assets before the crisis, but as soon as the crisis hit, high-IT adoption banks experienced a significantly smaller increase of NPLs compared to their peers. Regression analysis reveals that a one standard deviation higher pre-GFC IT adoption is associated with 16 basis points lower NPL to assets ratio in the years between 2007 and 2010. This represents a 10% reduction with respect to the cross-sectional average and 14% of the cross-sectional standard deviation. In the panel dimension, there is no significant correlation between pre-crisis IT adoption of banks and their non-performing loans outside the crisis. However, once the crisis hit, higher IT adoption predicts fewer NPLs: our estimates imply that if banks had a one standard deviation higher IT investment before the crisis, the surge in NPLs could have been lower by 15% with respect to pre-crisis levels.

The level of NPLs has widely been considered an important indicator for banking sector distress (Demirgüç-Kunt and Detragiache, 2002) and a strong increase is associated with severe adverse macroeconomic consequences (Peek and Rosengren, 2000; Caballero et al., 2008). Consistent with IT adoption partially shielding banks' ability to support the real economy, we find low IT banks tightened lending significantly more than high IT banks during and several years after the GFC.

We then explore the channels through which IT can enhance banks' resilience to the crisis. Using loan-level data on securitized mortgages, we find evidence in favor of improved borrower screening by high IT banks. Instead, we find no evidence for other potential explanations such as differences in business model or specialization, offloading of lower-quality loans, or enhanced monitoring.

Our main measure of IT adoption in banking is closely related to several seminal papers on IT adoption for non-financial firms, such as Bloom et al. (2012), Beaudry et al. (2010), Bresnahan et al. (2002), and Brynjolfsson and Hitt (2003). We access data on the number of personal computers (PCs) and the number of employees in a bank branch. Following this previous literature, we use the ratio of PCs per employee within a branch as the relevant measure of branch-level IT adoption. As the revolutionary power of IT stems from its being a multi-purpose technology, we follow this previous literature and study general adoption of information technology rather than specific technologies (e.g. ATMs, online banking, or Mortgage Electronic Registration Systems, as in Hannan and McDowell (1987), Hernández-Murillo et al. (2010), or Lewellen and Williams (2021)). Therefore, our analysis sheds light on the overall economic impact of IT adoption, rather than on specific IT applications. Nonetheless, we test the reliability of PCs as a predictor of the use of other IT technology. We confirm that there is a strong correlation between the share of PCs per employee and other measures of IT adoption, such as IT budget or adoption of frontier technologies in 2016; these alternative measures are unfortunately unavailable in our data before 2007.[1] To the best of our knowledge, this is the first paper to use this type of data to study financial firms.

We document that the most powerful predictor of a branch's IT adoption is the bank group it belongs to. We map the bank branches to Bank Holding Companies (BHCs) and estimate a BHC fixed effect after controlling for the geography of the branch (through county fixed effects) and other characteristics, such as the size of the branch. These fixed effects serve as our measure of IT adoption on the level of the BHC , which we also refer to as *bank* interchangeably in the text.

Pre-crisis technology adoption may be correlated with other bank characteristics which impact non-performing loans during the crisis. Most importantly, demand for IT equipment and its productivity has

[1] In fact, later waves of the same dataset provide additional information on IT-budget and adoption of Cloud Computing at the establishment level: the number of PCs per employee is a strong predictor of these other measures of IT adoption. For example, the correlation between the per capita share of PCs and the IT budget is 65% on the branch level data.

been associated with firms' organizational forms and managerial quality (Bresnahan et al., 2002; Bloom et al., 2012). Thus, the main concern for a causal interpretation of our results is that IT intense banks were simply "better run" and superior management practices shielded them from the impact of the crisis.

Our analysis uncovers several pieces of evidence in favor of a direct role of IT adoption, thus mitigating the concern that the correlation between IT and bank resilience is driven by unobservable factors, such as management quality. First, we find that our measure of IT adoption–which is purged of local variation and branch characteristics–is not significantly correlated with banks' ex-ante exposure to the GFC in terms of their geographical footprint or business model as measured by funding sources, assets composition, and other balance sheet characteristics. Our measure of IT is also uncorrelated with employees' average wages or executives' compensation, which can be thought of as measures of workforce human capital (Becker, 2009). The absence of a correlation between IT adoption and all these observable characteristics is a useful falsification test: it suggests that our measure is unlikely to be correlated with other unobservable predictors of exposure to the crisis.

Second, we find that the estimated impact of IT on NPLs is unaffected by the inclusion of a rich set of variables as controls. Exploiting this coefficient's stability, we follow Altonji et al. (2005) and Oster (2019) to provide formal testing for the presence of bias from unobservable bank-level characteristics, finding no evidence of a sizeable bias.

Third, we complement our analysis with a set of instrumental variable (IV) specifications based on the distance between a bank headquarter and land-grant colleges and universities. These institutions were established at the end of the nineteenth century in all US states to provide technical education. We show that their students are significantly more likely to major in technical subjects and less likely to major in business and management sciences, suggesting that these colleges are a shifter of the availability of technical knowledge rather than managerial capabilities. In addition, the location of land-grant colleges does not predict the presence of BHC headquarters in a county, indicating the distance between locations is independent with respect to the most relevant factors impacting the banking business. We then show that banks whose headquarters are closer to these colleges have generally a higher level of IT adoption, supporting the idea that technical knowledge is an important factor in fostering technology adoption. However, the explanatory power of the distance between a bank's headquarter and the closest land-grant colleges is low. We thus rely on weak instrument techniques which provide confidence intervals for causal effects in absence of a strong instrument (Andrews and Stock, 2018). The estimated intervals do not contain zero, rejecting the null of no causal impact of IT on NPLs, and confirming the main finding of the paper.

Fourth, to shed further light on the role of IT versus managerial quality, we study the biographies of the banks' top management. In fact, the personal characteristics and experience of leaders matter for the outcomes of their organizations (Benmelech and Frydman, 2015). We apply a simple text-analysis algorithm to the biographies of top executives hired before 2007. We search for specific tech-related keywords and use them to measure the managers' predisposition toward IT. We find that banks led by more "tech-oriented" executives adopted IT more intensively and were also more resilient in the crisis. Interestingly, when we estimate the impact of tech-savviness of executives over time, we find a strikingly similar pattern compared to the one estimated with the baseline measure of IT adoption: banks run by tech-oriented executives had statistically indistinguishable levels of NPLs compared to their peers in any year before the crisis; however, once the crisis hit, their NPLs increased significantly less than banks led by executives with no tech-background. The results hold after controlling for both their compensation and other characteristics, such as tenure or post-tertiary education. As long as executive "overall" quality is, at least partially, priced in their compensation, these results suggest that it is "tech orientation" that matters and not managerial talent. These findings support the hypothesis that IT adoption in banking, which can be partly caused by executives' personal experience and inclinations, led to more resilience during the crisis.

Adopting a "weight of evidence" approach, this collection of results points toward IT itself as the cause of lower NPLs rather than a spurious correlation between the two variables created by unobserved bank characteristics, such as managerial quality.

Turning to the mechanism through which higher IT adoption increases banks' resilience we test for four possible channels: (i) adaptation of the business model, (ii) offloading, (iii) monitoring, (iv) screening.

IT adoption may impact NPLs by changing banks' business model, for instance, if it increases banks' focus on market segments that are less affected by financial crises. We find no evidence for such a mechanism. We find instead that high IT adopters experienced lower NPLs during the GFC for any of the major loan categories (C&I, Commercial Real Estate, Residential Real Estate). Consistent, we find no correlation between originators' IT adoption and borrowers' credit score in the GSE data: high IT adoption banks do not simply focus on less risky market segments.

To test for the other potential channels, we analyze the performance of mortgages originated before 2007 and sold to Freddie Mac and Fannie Mae, the two large government-sponsored enterprises (GSEs). We find that mortgages sold by high-IT adoption banks were significantly less likely to become delinquent during the GFC than the ones sold by other banks, ruling out that high-IT banks simply offloaded worse loans and therefore had fewer NPLs on their balance sheet. This also implies that the better performance of high-IT adopters during the crisis is driven–at least in part–by the origination of better loans, leaving screening or monitoring as potential explanations. However, we find no evidence that the IT adoption of the mortgage servicer is associated with lower delinquency rate or higher modification probability of delinquent mortgages, pointing toward better screening rather than monitoring as the channel through which IT adoption increases bank resilience.

This result has important implications for financial stability. If high-IT adopters were only better at offloading their bad loans to GSEs, then IT intensity would lead to risk-shifting and exacerbate moral hazard, rather than enhance financial stability. This is an important concern because securitization may reduce the incentives of banks to screen and monitor borrowers (Keys et al., 2009, 2010, 2012) and IT adoption may facilitate securitization. A related concern is those high-risk individuals, which were rejected by technology adopters, borrowed from banks with less IT operating in the same area. We test for these spillover effects and find no evidence, either. Both of these results suggest that IT adoption had positive aggregate effects on the stability of the financial system and was not associated with a transfer of risk across parties.

We further highlight the financial stability implications of IT in banking by providing evidence that technology adoption in banking does not only lower the NPLs on the balance sheet of the bank but also increases their lending volumes during the crisis. These positive real effects suggest that the recent rise in FinTech could be beneficial for financial stability through better screening abilities.

Related Literature This paper is related to the finance literature on technology adoption, which has been thriving in recent years thanks to the surge of FinTech (Fuster et al., 2018, 2019; Berg et al., 2019; Di Maggio and Yao, 2021; Buchak et al., 2018, e.g.). We contribute by evaluating the impact of IT adoption in lending on financial stability and by studying the impact of technology across a sample that covers the majority of US bank lending.

Close to us are a few papers that analyze certain features of IT adoption in banking during normal times (Hannan and McDowell, 1987; Berger, 2003; Bofondi and Lotti, 2006; Hernández-Murillo et al., 2010; Bostandzic and Weiss, 2019; D'Andrea and Limodio, 2019; He et al., 2021). We contribute by focusing on the effect of overall IT adoption across banks on their performance when a system-wide shock hits. More recently, a few studies have followed our approach to study the role of IT during the COVID-19 pandemic and found that banks adopting IT more intensely performed better even in a crisis of non-financial nature (Branzoli et al., 2021; Kwan et al., 2021; Dadoukis et al., 2021) and that firms' IT fosters the resilience of the local labor markets (Pierri and Timmer, 2020).

We also provide direct evidence that IT adoption ameliorates the screening of borrowers, consistent with the literature on information in lending which argues that advances in IT improve the processing of information by helping firms to gather, store, distribute, and analyze information (Liberti and Petersen, 2018; Petersen and Rajan, 2002; Degryse and Ongena, 2005; Petersen and Rajan, 1994).

The rest of the paper is structured as follows. In section 2 we describe the several databases used; in section 3 we present the main results on IT adoption and NPLs; in section 4 we provide evidence on the roots of IT adoption and propose an instrumental variable strategy; in section 5 we present additional results on mortgages performance to shed light on potential mechanisms; in section 6 we conclude.

2 Data and Measurement

IT Adoption The IT data comes from an establishment survey on personal computers per employee by CiTBDs Aberdeen (previously known as "Harte Hanks") for years 1999, 2003, 2004, 2006, and 2016. For the year 2016, we also have information on the IT budget and the usage of cloud computing of the establishment. The data also contains information about the type of establishment–i.e. whether it is the headquarter (HQ), a branch, or a back-end office–the number of employees in the establishment as well as the location. The correlation between the IT budget of the establishment and the number of computers as a share of employees is very strong for later years, e.g. 65% in 2016. There is also a positive correlation between PCs per Employee and the adoption of cloud computing. These correlations provide assurance that the number of personal computers per employee is a good measure of IT adoption, even more recently, but likely even more so in earlier years when other forms of IT adoption were less common. (As a further check, we use OECD data on businesses' use of technologies in different countries, size categories, and industries, and see a strong correlation between the use of PCs by employees and various other IT measures, such as the use of broadband connections, Big Data analytic, or Cloud Computing, as graphically illustrated by Figure A1.)

We focus only on establishments in the banking sector (based on SIC2 classification) and drop savings institutions and credit unions (based on SIC 3). After these cleaning steps, we end up with 143,607 establishment-year observations. We map bank branches from the Aberdeen dataset to the BHC data by using banks' names and the BHC structure.

Our measure of IT adoption is based on a regression of the share of personal computers on a bank fixed effect controlling for the geography of the establishment and other characteristics. By doing so we can control for several characteristics that may be correlated with the number of personal computers per employee of the bank but are not informative about whether the bank has been at the technological frontier. This approach follows Beaudry et al. (2010), who measure IT adoption on the region-level controlling for establishments' industry and size. We estimate the following regression for the years 1999, 2003, 2004, and 2006:

$$PCs/Emp_{i,t} = \widetilde{IT_b} + \theta_{type} + \theta_c + \theta_t + \gamma \cdot Emp + \epsilon_{i,t} \tag{1}$$

where $PCs/Emp_{i,t}$ is the ratio of computers per employee in branch i survey wave t (capped at top 1%), $\widetilde{IT_b}$ is a bank (i.e. BHC) fixed effect, θ_{type} is a establishment-type (HQ, standalone, branch) fixed effects, θ_c is a county fixed effect, θ_t is a year fixed effect and Emp is the log number of employees in the establishment.

The R-squared of the regression is 42%. The main part of the explained variation is captured by the bank fixed effect (60%). The location of the establishment explains 27% of the variation, year fixed effect explains 11%, while number of employees' and establishment types have smaller explanatory power.

Our measure of IT adoption, IT_b hereafter, is a standardized version of the bank fixed effect. It is obtained by dividing $\widetilde{IT_b}$ by its standard deviation after subtracting its mean. This adjustment is done considering the summary statistics for the sample of banks that we are able to match with BHC data only. The bottom panel of Figure A2 plots the cross-sectional distribution of IT_b. For each BHC, we also constructs the IT adoption of other banks operating in the same location.

Regulatory Data on BHCs We use bank balance sheet information from bank holding companies (BHCs) to assess the resilience of banks to the GFC. The data is collected by the Federal Reserve Bank of Chicago. We use the Financial Institution Reports which provides consolidated balance sheet information and income statements for domestic BHCs.

Our main dependent variable is the amount of NPLs scaled by total assets.[2] We check the robustness of the main results of the paper to other definitions of NPLs (e.g. including loans with shorter delinquency periods) and alternative scaling choices (e.g. the use of loans as denominator), see section 3.[3] Figure A2 shows the distribution of the average NPLs ratio between 2007 and 2010 across banks. Most banks have an NPL ratio of around 1% in the crisis period, but there is a long right tail in the distribution. For some banks almost 5% of their balance sheet consists of NPLs.

In addition to NPLs we construct the following variables as bank-level controls. The share of loans over total assets ($Loans$), the log of assets (in thousands of US Dollars) ($Size$), equity over assets ($Capital$), wholesale funding over assets ($Wholesale$), the return on assets (ROA), and the average log wage paid to employees (in thousands of US Dollars) ($LogWage$). All variables are averaged between the years 2001 and 2006. We winsorize all bank-level ratio at top 2.5 percent before taking averages, but results are robust to different treatment of outliers.

Our sample is composed of BHC which we can merge by name with the IT Aberdeen data and such that all the controls variable described above are non-missing. The sample covers about 80% of all pre-GCF bank lending, and even more fore C&I and Residential Real Estate loans (see Figure A3). We also match 77 out of the 100 largest BHC in terms of 2006 loans.

Biographies of Executives We obtain data on the biography of executives from S&P Global Market Intelligence. We have information on the Chief Executive Officer, the Chief Financial Officer, the Chief Operating Officer, and the President of the bank. We focus on the executives that have been hired before the GFC. We search the biography for the following words to characterize whether an executive is tech-prone: technology, engineering, math, computer, machine, system, analytic, technique, method,

[2] Our baseline NPLs are defined following Hirtle et al. (2018): Total loans, leasing financing receivables and debt securities and other assets - past due 90 days or more and still accruing (bhck5525) + Total loans, leasing financing receivables and debt securities and other assets - nonaccrual (bhck5526) - Debt securities and other assets - past due 90 days or more and still accruing (bhck3506) - Debt securities and other assets - nonaccrual (bhck3507).

[3] We rely on assets as a scaling variable for NPLs (rather than loans) since lending is endogenous to IT adoption and NPLs during the crisis, as we document in subsection 3.4. Moreover, assets are commonly used to normalize the bank-level variables. The main raw patterns and results are robust to using loans instead of assets to normalize NPLs.

process, stem, efficiency, efficient, software, hardware, data, informatic. We count the number of occurrences of these words for each executive in the biography and scale the number by the total number of words in the biography. For each bank, we take the average across executives to construct a bank-level measure of the IT intensity of their executives. In addition to the biography, we also use data on the total compensation of the executives from the Standard & Poor's Executive Compensation database.

House Price, Land-Grant, and County-level Data We compute BHCs' exposure to the downturn in house prices, $HP\ Exposure$. We obtain county-level home value index from Zillow. For each county we construct the (opposite of) percentage change in house prices from 2007 Q4 to 2012Q3. For each BHC we compute the weighted average decrease in house price where the weights are the local footprint of the BHC across counties, as measured by deposits in the FDIC dataset.[4]

We obtain the list of all the 70 land-grant colleges (and universities) established in the US states during the nineteenth century (1862 and 1890) from the website of the US Department of Agriculture. We obtain data on enrolment by major and test scores from IPEDS (Integrated Postsecondary Education Data System) survey for 1996 and 2018 for several higher education institutions. We obtain county-level demographic characteristics from the 2000 US Census and from the American Community Survey from 2001 to 2006. We obtain information on employment by industry in each county from the Quarterly Workforce Indicators (we set these variables equal to national average for counties outside the dataset, e.g. in Puerto Rico). County-level variables are averaged between 2000 and 2006.

GSE Data As Hurst et al. (2016) we pool data from Freddie Mac's Single Family Loan-Level Dataset and Fannie Mae's Single Family Loan Performance Dataset. These loan-level datasets covers the performance on mortgages that the two GSEs bought starting in 1999. The data includes higher-quality loans which had to conform to agency guidelines (Adelino et al., 2016).

3 IT adoption, NPLs, and Lending

In this section, we investigate the relationship between banks' IT adoption before the GFC and their NPLs during and outside the crisis. As a preview, Figure 1 shows the evolution of the ratio of NPLs to assets

[4] We take the average deposits across the pre-crisis years. For three BHC, which we do not merge to the FDIC dataset, we use instead the IT establishment data to compute the local footprint.

from 1996 to 2014 for banks in the bottom and top quartile of the IT adoption distribution. This raw data shows that the two series are virtually indistinguishable until 2007. However, in 2008 –as NPLs start to surge– the two lines diverge. The growth in NPLs is considerably more pronounced for banks with low IT adoption. The NPLs peak in 2010 and the two series start converging again from 2011.[5]

3.1 Panel

In our sample, the sharp rise of NPLs over assets occurred in the years from 2007 to 2010. Therefore, we define these years as the "crisis" period. To investigate whether banks with different levels of IT adoption experienced different levels of NPLs during this period, we rely on the following panel equation:

$$NPL_{b,t} = \alpha_b + \delta_t + \beta IT_b \cdot crisis_t + (X_b \cdot crisis_t)'\gamma + \epsilon_{b,t} \tag{2}$$

where $NPL_{b,t}$ is the share of non-performing loans relative to assets for bank (BHC) b in year t. IT_b is our bank-level measure of IT adoption before the crisis as defined in section 2, α_b and δ_t are bank and year fixed effects, respectively. The former capture bank time-invariant heterogeneity while the latter capture time-varying aggregate shocks, such as business cycle fluctuations. X_b is a vector of bank-level variables (pre-crisis averages) that may be associated with NPLs during the crisis, as described in section 2. We include observations for years between 2001 and 2014 and keep only observation for which we have all the variables in X_b. We are left with 4,608 observations on 337 banks.

Table 1 presents the results from estimating different versions of Equation 2 via OLS, together with standard error double-clustered at the bank and year level. We first present a less saturated version of the above equation. Column (1) shows the result of Table 1 without the inclusion of bank fixed and year fixed effects as well as without controls. The base effect of technology adoption on non-performing loans is negative but small and not statistically significant. We do not find that IT adoption significantly affects non-performing loans during normal times. However, the interaction between the crisis dummy and IT adoption is negative and statistically significant. In the time of the crisis banks that adopted more IT before the crisis had a significantly lower share of non-performing loans than banks with less IT adoption. This result is robust to the inclusion of bank and year fixed effects and various controls. In

[5] The dynamics of NPLs for a bank with intermediate adoption lies between the low- and high- adopters in most years, see Figure A4. To check that this pattern is mainly driven by the numerator of the series (NPLs) rather than the denominator (Assets), we fix the value of assets to the bank-specific pre-crisis average and plot the adjusted ratio in Figure A5, finding a very similar pattern.

addition, the coefficient is stable across specifications, suggesting a low correlation between the controls included and the measure of IT adoption. A one standard deviation higher IT adoption is associated with a between 13 and 17 basis points lower NPL share increase during the crisis. The average share of NPLs was 1.5 percent in the crisis period, while its standard deviation was 1.13. Therefore, a one standard deviation higher IT adoption led to a reduction in NPLs between 9 and 11% with respect to the mean and between 12 and 15% with respect to the cross-sectional standard deviation. Moreover, the increase between the pre-crisis average and the crisis NPL share is 1.05 percentage points. Therefore, if we ignore potential heterogeneity in the effect of IT adoption, spillover between banks (which we test for, see below), and general equilibrium effects, we find that a one standard deviation uniform increase in IT adoption across all banks would have diminished the surge in NPLs between 12 and 16%.

Columns (5) introduces additional controls to the baseline specification with only bank and year fixed effects, leaving our results unchanged. For brevity, we only display the IT of local competitors as a control variable to shed light on whether there are negative spillover effects of IT adoption on other banks. Individuals who want to borrow but are rejected by a high-IT bank could apply for a loan at a low-IT bank in the same area. If the low-IT bank does not identify the borrower as risky, the bank may grant a loan, which defaults during the crisis and leads to an increase in NPLs for this bank. If this mechanism is at work, we would still find a significant difference between high- and low-IT banks in terms of their NPLs during the crisis, but the aggregate increase in NPLs would be the same if all banks adopted more IT with ambiguous implications for financial stability. However, the interaction shows that banks, which are based in areas where their competitors adopted more IT, did not suffer a stronger increase in their NPLs relative to other banks. This evidence suggests that IT adoption does not have negative spillover effects on local competitors. Finally, a battery of robustness tests are reported in Table A1, confirming our results.[6]

Next, we allow the impact of pre-crisis IT adoption on NPLs to vary each year between 1996 and 2014 by year by estimating the following equation:

$$NPL_{b,t} = \alpha_b + \delta_t + \sum_{\tau \neq 2006} \beta_\tau \cdot IT_b \cdot 1[t = \tau] + \epsilon_{b,t} \tag{3}$$

[6]For instance, in a robustness exercise we use a BHC-level bootstrap procedure to re-estimate the standard errors, finding very similar t-statistics as those in Table 1 (see column 10 of Table A1). Because this procedure re-estimates the IT measure for each of the bootstrap samples, it addresses the concern that our standard errors suffer from a "generated regressor" problem.

The coefficient of 2006 is normalized to zero. Results are illustrated in Figure 2. The effect of IT adoption on NPLs is insignificant in the pre-crisis period between 1996 and 2007, except for a small negative effect which is statistically significant at the 5% level in 2002, likely due to the early 2000 recession. As shown in Table 1 banks which adopted more IT before the crisis had significantly lower NPLs than their counterparts in the crisis. In particular, between 2007 until 2010 the effect is negative and statistically significant at the 5% level, and in 2009 and 2010 the effect is even statistically significant at the 1% level. The coefficient reaches its maximum in 2010 with -0.3. In other words, a one standard deviation higher IT adoption was associated with 30 basis points lower NPLs in 2010. The impact is still negative in 2011 and 2012 although not statistically significant anymore. We detect no impact in the two latest years of the sample, 2013 and 2014.

3.2 Cross-sectional analysis

In this section, we analyze the relationship between bank-level IT adoption and various other bank characteristics in the cross-section.

We apply OLS to the following equation:

$$Y_b = \alpha + \beta \cdot IT_b + \epsilon_b \tag{4}$$

where Y_b is either the share of NPLs over assets in the crisis period or one of the control variables in the set X_b described above and the independent variable is the pre-crisis IT adoption. Collapsing the data in this avoids the underestimation of standard errors that can arise when estimating a diff-in-diff specification using panel data (Bertrand et al., 2004).

Table 2 presents the results. Consistently with the panel (Table 1 and Figure 2) technology adoption is strongly negatively correlated with NPLs in the crisis period (column 1) with an R-squared of 2.6%. The magnitude of the coefficient (18 basis points) is slightly higher but similar to the one estimated in the panel regressions.

Columns (2)-(8) test whether IT adoption on the bank level is correlated with other bank-level variables–described in section 2–that could be important in driving NPLs in the post-crisis period. We find that IT adoption is not significantly related to any of these characteristics.[7] Moreover, the R-squared of column

[7] We compute additional variables, such as the share or residential or personal loans over the total amount of loans, and find

(1) is much larger (at least 4 times) than the ones of columns (2)-(8). We, therefore, conclude that IT adoption is not correlated with any important bank-level characteristics that could predict their exposure to the GFC. This result is a comforting "balancing" test since it suggests IT is unlikely to be correlated to other unobservable characteristics that would also make them more exposed to the financial shocks and related recession.

The (counterintuitive) lack of correlation between IT adoption and pre-crisis ROA is in line with previous literature which documents weak productivity gains from IT in banking in normal times (Beccalli, 2007), and a negative or null correlation between profitability and adoption of ATM or online banking (Hannan and McDowell, 1984; Hernández-Murillo et al., 2010). We do not find evidence that bank size is a determinant of branch-level IT adoption. Kovner et al. (2014) document sizeable economies of scale (also) for IT expenditure. This may be due to the fact that larger buyers can bargain for lower prices. Our measure, however, captures IT equipment, not IT expenditure. While expenditures have the advantage to convey, through prices, some information on the quality (and novelty) of IT purchases, looking only at the quantity of PCs avoids the bias that may be caused by the heterogeneous purchasing power related to bank size. Other studies found that the timing of the adoption of a specific technology is usually faster for larger banks (Hannan and McDowell, 1984; Hernández-Murillo et al., 2010). Those studies, however, focus on very coarse adoption variables (have any ATM or not, have a website or not) and are therefore prone to reward larger banks; our IT variable, instead, aims to capture how widespread is the general use of computational systems within a bank branches network by measuring the availability of equipment *per employee*.

It must also be noticed that our measure of IT adoption is purged by local variation (and branch characteristics) to eliminate potential confounding factors clustered at the local level and do not compare banks operating in very different parts of the country (our main results are robust not to perform such adjustments, see Table A1). Thus, the lack of correlation with other characteristics does not necessarily imply a lack of correlation with the row proxies of IT adoption.

In column (10) we include all the bank characteristics as controls in a regression of post-crisis NPLs on IT adoption. We find a very small change in the coefficient of IT adoption, despite the seven-fold increase in R-square. This suggests that the equation of column (1) does not suffer from an omitted

no correlation of these variables with IT adoption either. Additionally, in section 5 we present direct evidence that the impact of IT on NPLs is not driven by the location of lending activities.

variable bias and points towards a causal relationship between IT adoption and NPLs (Altonji et al., 2005; Oster, 2019), which we also test formally following Oster (2019) and find that our results are robust to the presence of unobservable variables.[8] column (9), instead, shows a positive correlation between a BHC's IT adoption and IT of local competitors.

3.3 Loan Categories

Which loan categories are responsible for the lower NPLs during the crisis? For most of BHC in our sample, we can compute NPLs across three different loan categories: residential real estate, commercial real estate, and C&I lending. As reported by Table 3, high IT adoption banks reported lower NPLs on their balance sheet in all three categories. The results hold whether we normalize the NPLs by the loans in the same category or by the total assets.

These findings suggest that the lower NPLs for high IT adoption banks (Table 2) are not driven by the fact that IT changed banks business model and induces them to focus less on lending categories that were more impacted by the crisis, such as commercial real estate. These results also highlight that IT has played an important role not only for banks lending to households but also for corporate credit (Petersen and Rajan, 2002; Ahnert et al., 2021; He et al., 2021).

3.4 Bank Lending

High levels of NPLs weigh on banks' profitability and can constrain their lending, depressing real economic activity. As IT adoption improves banks' resilience, it may also shield their ability to provide credit to customers during (and right after) financial turmoil.

Figure 4 reports the share of total loans (normalized by pre-GFC assets) for banks in the high- and low- IT adoption groups from 2001 to 2014. The two series are indistinguishable up to 2006, consistent with IT not being a very important factor in the pre-crisis period. From 2007 on, the amount of loans provided by low-IT adopters is remarkably lower than the one provided by the more IT-intense counterparts. The two series start converging in 2012 but the difference is still present in 2014. These patterns,

[8] In fact, Oster (2019) provides formal statistical procedures to assess the stability of OLS coefficients to the inclusion of relevant control and test for the potential bias arising from the presence of other unobservable variables. Following Oster (2019) jargon, we set the "hypothetical R-square" to 1, which is the most conservative choice. We find a relative degree of selection above 1, indicating that, under the assumption of "proportional selection of observables and unobservables" (Altonji et al., 2005; Oster, 2019), the impact of IT adoption on NPLs cannot be non-negative. That is, the values of the OLS coefficient compatible with additional unobservable covariates are all below zero.

which are confirmed by regression analysis (see Table A2), indicate that heterogeneity in IT adoption, arguably through the impact on NPLs documented in section 3, helped banks providing credit during (and after) the GFC. This suggests IT in banking can have an impact on the real economy.

4 The Roots of IT Adoption

Why do some banks adopt less IT than others despite its beneficial effects?

Economists have documented that frictions of different nature–such as lack of information or agency frictions (Bloom et al., 2013; Atkin et al., 2017)–can prevent or slow down firms' adoption of beneficial practices and technologies. In this section, we study two factors that could help overcome these frictions and foster banks' IT adoption: the background and personal inclination of a BHC top executives and the closeness of its headquarters to the land-grant colleges established in the nineteenth century across the United States. The focus on the bank's top executives and headquarter location is based on the descriptive patterns documented in section 2: the explained variation in technology adoption at the branch-level is driven by BHC characteristics (60%) relative to geographic characteristics (27%).

4.1 Executives' Background

The characteristics and background of top executives impact firms' outcomes (Benmelech and Frydman, 2015; Bertrand and Schoar, 2003). We consequently conjecture that top executives with a more tech-prone background and orientation may promote a higher degree of IT adoption in the banks they lead. To capture the tech orientation of the top executives (CEOs, CFOs, COOs, and Presidents) hired before 2007, search for tech-related keywords in their biographies (see section 2). We extract several other characteristics from the biographies, such as whether they obtained a post-graduate degree (Ph.D. or Master's), how long they have been in their current position (tenure), their age, their gender, and whether they have an educational background in management or business administration (e.g. completed an MBA). Lastly, we obtain data on their total compensation from the Standard & Poor's Executive Compensation database. We then average these variables for each bank group and match regulatory data, executive biographies, and salaries for 156 BHC.

To test our conjecture, we then estimate the following cross-sectional regression model:

$$Y_b = \alpha + \beta ExecIT_b + X_b'\gamma + \epsilon_b \tag{5}$$

where b is a bank in our sample, $ExecIT_b$ is the "tech-orientation" of b's executives, and the dependent variable Y_b is either the level of NPLs over assets during the crisis period or the pre-crisis IT adoption. Results are presented in Table 4. Column (1) shows a positive association between the tech orientation of the executives and our baseline IT measures. Column (2) shows that banks led by more tech-oriented executives experienced lower NPLs during the crisis. Column (3) shows that banks with higher-paid managers have also lower NPLs during the crisis, indicating that executives with more human capital performed better during the crisis. The impact of "tech-orientation" may thus be due to–for instance–better management practices unrelated to IT itself. In column (4) we add both variables to the regression and find that–once we control for tech-orientation–the impact of compensation is not statistically significant anymore and instead dominated by the tech-savviness of the executives: it is specifically the tech-orientation, and not general quality or skills, that matters for bank performance during the crisis. In columns (5) and (6) we additionally control for other characteristics of the executives, leaving our coefficient of interest on the tech-orientation statistically significant (the bank controls of Table 2 are also added, but coefficients are left unreported). Interestingly, while most of the characteristics of the executives do not seem to play a role for the bank performance during the crisis, we find evidence that banks that had more women and younger leaders among the top executives experienced fewer NPLs. These findings are consistent with tech-savvy executives boosting the adoption of IT which, in turn, improves banks' performance during the crisis. The interpretation of tech-savviness as a root of IT adoption comes with the caveat that an alternative explanation is that banks more prone to IT are also more likely to hire/promote more tech-prone executives.

We also reestimate Equation 3, which sheds light on the time-varying impact on IT adoption on NPLs, replacing our baseline IT measure with the tech orientation of the executives. Figure 3 shows strikingly similar results. Banks led by more tech-oriented executives experienced a significantly more limited increase in NPLs during–and right after–the GFC. The results are also similar in terms of economic magnitudes. While a one standard deviation higher IT adoption using our baseline measure is associated with 30 basis points lower NPLs during the peak of the crisis, a one standard deviation higher IT adoption in terms of the tech-savviness of the managers is associated with 21 basis points lower NPL ratio. A similar pattern emerges from the raw data (Figure A6).

4.2 The Land-Grant Colleges

In this section, we study a potentially exogenous shifter of technical knowledge and inclination of banks' headquarter decision-makers and other employees. The Morrill Act of 1862 endowed federal land to states to found universities. The focus was to teach science, agriculture, and other technical subjects, due to a nationwide demand for more technical skills. While some land-grant universities offer nowadays degrees in both arts and science, their focus remains on technical subjects. Indeed, in appendix A1 we show that students at land-grant colleges and universities are still much more likely to major in engineering and less likely to major in non-technical fields, such as education or business. We also find that SAT scores in math are higher for students of land-grant university students, but their writing scores are not.

The presence of land-grant universities has been used as an instrument for the supply of skilled labor in a metropolitan area (Moretti, 2004) as their exact location is largely due to historical accidents.[9] The location of many banks' headquarters is also related to their historical heritage and usually predates the IT revolution.[10] For instance, Bank of America's headquarter location in Charlotte (North Carolina) was established in 1874 by the foundation of the "Commercial National Bank" (Blythe and Brockmann, 1961). More generally, the presence of a BHC headquarter in a US county is uncorrelated with the presence of a land-grant college (see appendix A1), indicating land-grant location is plausibly exogenous with respect to the most important factors affecting the banking industry and headquarter choice.

Land-grant colleges and universities can impact the technical knowledge and inclination of decision-makers–and thus their attitude towards more aggressive adoption of IT–in several ways. Directly, by increasing the likelihood of hiring workers that are more tech-inclined as graduates of these institutions are more likely to directly be part of the headquarter personnel. But also indirectly, through spillover of knowledge and ideas from the campuses.

As many socio-economic phenomena, including internal migration or knowledge and technology

[9] As an example, the choice of Ithaca over Syracuse for the establishment of Cornell University was due to the fact that one of the two founders was robbed while visiting Syracuse (Andrews, 2019). Land-grant colleges are distributed evenly within a state and independent of Census regions, and not established in areas that were richer due to natural resources or other factors; workers in areas close to a land-grant college are shown to be similar in terms of racial and demographic characteristics and have very close Armed Forces Qualification Test scores for a given level of education (Moretti, 2004; Shapiro, 2006)

[10] For each BHC, we take the headquarter county from regulatory filings in 1995 or earliest available year.

diffusion, tend to follow gravity-like patterns (Keller, 2002; Santacreu, 2019), our specification adopts a gravity approach to incorporate both channels: we compute the set of variables $D_{b(c),j}$, which are equal to the distance in log miles (plus one) between the county of each land-grant college j and BHC's headquarter county, weighted by the log size of the college (STEM enrollment).

Under the assumption that land-grant colleges impact banks' performance during crises only because they foster their technology adoption, $D_{b(c),j}$ can be used as a set of instruments for Equation 4. As closeness to these colleges increases the education of the local labor force, an obvious threat to this exclusion restriction is that banks lend in areas close to their headquarter and these areas are more resilient to shocks through the effect on overall education and economic prosperity. Since we focus on BHC, whose lending portfolio is usually geographically diversified, this is less of a concern than if we were to focus on smaller banks. We further mitigate this concern by controlling directly for local education, household income, county size, and population density of the county where the BHC is headquartered. We also add state fixed effects, so we compare BHCs headquartered in the areas that are similar for the level of education, income, and density, are in the same state, but that have different exposure to technical knowledge because of the land-grant colleges. We also control for the share of employment in manufacturing and construction, because the former is a sector that suffers more during recessions, while the latter played a particularly important role during the GFC. Finally, the finding that these colleges have fewer students majoring in business and management science mitigates the concern that they impact banks through better management practices rather than IT adoption.

We implement the IV empirical strategy by estimating the following 2SLS model:

$$IT_b = \delta + \sum_j \rho_j \cdot D_{b(c),j} + X_b'\gamma_{1s} + \eta_b \tag{6}$$

$$NPL_b = \alpha + \beta \cdot IT_b + X_b'\gamma_{2s} + \epsilon_b \tag{7}$$

where X_b includes the usual set of bank-level pre-crisis controls, plus the set of county-level controls. Including all colleges j into the first stage could be problematic both statistically and economically, we thus pick only the three closest to each BHC's headquarter: in the appendix (Figure A9) we illustrate the negative correlation between the average $D_{b(c),j}$ for the three closest colleges to $b(c)$ and IT adoption, and also a positive correlation with NPLs during the crisis.[11] 2SLS are reported by Table 5: we estimate a

[11]As an alternative way to test the plausibility of the inclusion restriction we estimate the set of equations: $IT_b = \delta + \rho_j \cdot$

negative and large coefficient of IT adoption on BHC NPLs during the crisis (column 1). The inclusion of the controls (columns 2 to 4) decreases the size of the estimated coefficient by about 30%. The coefficient of column (2), while larger than OLS (-0.168), is not statistically different from it (p-value 12%). Similar results are found by using only the closest two colleges or excluding BHC headquartered on the West Coast, Alaska, Hawaii, or Puerto Rico. Therefore, the farthest away part of the country or the less densely populated West Coast does not drive the results. While these results are in line with the OLS analysis, the effective F-stat by Olea and Pflueger (2013), which is recommended in multiple instruments setting (Andrews and Stock, 2018), is well below the rule-of-thumb threshold of 10, revealing a weak instruments problem.

Because our instruments are weak, we apply weak instrument techniques following Andrews and Stock (2018). Rather than producing point estimates, these techniques aim to provide confidence intervals for the parameter of interest while taking into account the extra variability introduced by the low power of the first stage. Each point is included in the set if a certain statistical test cannot reject that value for the parameter (i.e. constructed through "test-inversion"). As there is no consensus on the best test to apply in our setting (multiple instruments and lack of homoskedasticity), we use four tests proposed by the literature (Moreira, 2003; Andrews et al., 2006; Andrews and Stock, 2018): the Wald test, the conditional likelihood ratio test, the K, and the K-J tests.[12] Table 5 reports these intervals, using 90% and 95% confidence levels. Such intervals are large, as intuitively expected given the low F-stat. However, they all reject the null of a zero (or positive) impact of IT on NPLs during the crisis, with one exception (out of 16) of the 95% confidence intervals, providing no evidence for the concern that OLS estimates are solely driven by some spurious correlation.

In conclusion, the land-grant IV analysis presents some limitations. In particular, the weak IV techniques only provide confidence intervals and do not offer point estimates for the 2SLS regressions. Also, stronger technical knowledge of the workforce could improve the organizational quality of the firm in general, improving their ability to screen, and its resilience during a crisis. This analysis nonetheless offers additional empirical support for the claim that technology adoption can have a causal impact on NPLs during a crisis.

$D_{b(c),j} + \epsilon_{b,j}$ where $j = 1, ..70$ is one of the land-grant colleges. We find that ρ_j is statistically different than 0 in 32 cases out of 70 and it is negative 90% of these cases.

[12] The Wald is not suited for case of weak instruments so it is reported only for illustrative purposes.

5 Loan-Level Analysis

To shed further light on the channels through which high-IT adoption banks were able to limit the surge in NPLs, we study the performance and characteristics of mortgages originated by banks with heterogeneous degrees of IT adoption and sold to GSEs. We pool loan data from Freddie Mac and Fannie Mae Single-Family Loans Datasets and estimate the following loan-level linear probability model:

$$Delinquent_l = \alpha_{z(l),o(l)} + \beta \cdot IT_{b(l)} + X_l' \gamma + \eta_l \tag{8}$$

where l is a mortgage held by a GSEs and originated between 2000 and 2006 by a commercial bank in our IT sample; $Delinquent_l$ is a dummy variable indicating whether the loan has ever been delinquent (past due 90 days or more) up to 2010. IT_b is bank-level technology adoption of the seller banks. X_l is a vector of mortgage characteristics at origination. It includes borrower's FICO score, Loan-to-Value (LTV) ratio, and Debt serving-to-Income (DTI) ratio, a dummy variable for multiple borrowers, a set of fixed effects for the origination channels and the mortgage purpose. We also include $\alpha_{z(l),o(l)}$, a set of fixed effects for property's zipcode interacted with the origination year to control for local heterogeneity that can arise, for instance, from the severity of the GFC and or from different house market dynamics.

Columns (1)-(4) of Table 6 reports OLS estimates of Equation 8, together with standard error clustered at the seller level with the dependent variable multiplied by 100.[13] Column (1) reports that mortgages originated by banks with a one-standard deviation higher IT adoption are 0.12 percentage points less likely to be delinquent, or 1.6% of the average (which is 7.4 percentage points). In column (2) we allow the coefficient of IT adoption to be different for borrowers above and below the median credit score (735), finding that only mortgages given to relatively riskier borrowers are impacted by lenders' IT adoption. In column (3) we expand the sample to include all mortgages originated since 2000, finding qualitatively similar results. The number of banks in the sample increases to 27 from 18 in columns (1) and (2), expanding the variation used to estimate the relationship between IT and mortgage performance.

These results highlight that at least part of the effect we document in subsection 3.1 is due to the origination of more resilient loans before the crisis. Importantly, it shows that high-IT adoption banks were not offloading low-quality loans to GSEs. If technology-prone banks were simply better able to securitize and offload their bad loans, IT adoption would lead to lower on-balance sheet NPLs during

[13] Alternative ways of clustering, e.g. on the state or postal code level, lead to smaller standard errors.

the crisis, without reducing the amount of NPLs in aggregate (Acharya et al., 2013). If this was the case, technology adoption would only lead to risk shifting and increase moral hazard issues and would not enhance financial stability.

However, the impact of IT adoption on the delinquency of mortgages offloaded to GSEs is much smaller than the impact on NPLs kept on the balance sheet (9.5% of the mean, see Table 3). This is consistent with high IT banks offloading mortgages which are worse than what is held on their balance sheet. As the original pool of originated mortgages is better to start with, arguably because of better screening, even these "negatively" selected mortgages are better than the ones offloaded by low IT banks.

We then ask whether the better loan performance derives from better borrower screening or ex-post monitoring. Agarwal et al. (2017) document a large dispersion across mortgage servicers in the take up of HAMP, a very large publicly-funded home modification program, potentially impacting loan performance. The authors also conjecture that part of this heterogeneity in loan modifications could stem from differences in IT investments. In column (4) we thus include the IT adoption of the firm that services the loan, which we can match to the IT data for most of the sample. We find no evidence that mortgages serviced by high IT firms are less likely to become delinquent. Such test however has two limitations: about 90% of loans are serviced and sold by the same bank, so estimating variation is limited, and loan modification–which can help limiting lender's losses–often happen after the loan has become delinquent. In column (5) we restrict our sample to only loans that have been delinquent and show that mortgages handled by high IT adoption servicers are not more likely to be modified (anytime up to 2010). Therefore, the results in column (4) and (5) point towards screening rather than monitoring as being an important factor in determining high IT banks' performance during the crisis.[14]

In the last column, we test whether banks with different IT adoption focused on different segments of the mortgage markets. We find no evidence that borrowers with different credit scores were served by banks with different IT. This is additional evidence against the potential explanation of our findings that IT changed banks' business model and make them focus on less risky borrowers. We find, instead, they were better at screening borrowers, especially among the higher risk segment.

As the correlation between IT and NPLs (and other measures of bank performance) outside the crisis is small and insignificant (see Table 1 and Table 2), improvements in screening appear to be particularly

[14]For example, more IT might have allowed these banks to sustain more reliable internal rating systems. We refer to Berg (2015) and Berg et al. (2020) for a description of internal rating systems.

valuable when overall delinquencies rise, boosting NPLs and hampering banks' performance. The banks that have better screening ability–such as the banks that invested more on IT–are able to limit the rise in delinquency and keep lending to the real economy.

The mortgage data allows us to control for additional characteristics of the loan, which also sheds more light on the channel through which IT adoption can affect NPLs, such as the postal code of the underlying property and the year of origination. The results confirm that the impact of IT adoption on NPLs is not fully driven by high-IT adopters lending to areas that were hit less by delinquency and foreclosures or originating a larger amount of loans in a particular year.

6 Conclusion

As the financial industry becomes more and more reliant on Information Technology, it is extremely policy-relevant to understand the consequences for financial stability of a more intense use of technology in lending decisions.

In this paper, we measure the heterogeneous degree of IT adoption of US commercial banks before the GFC using a novel dataset. We show that high-IT-adopters experienced a significantly smaller increase in NPLs on their balance sheets and provided more credit to the economy during the crisis. We present evidence pointing towards a causal impact of IT on banks' performance during the crisis. We evaluate different potential mechanisms for the impact of IT, including better screening of borrowers, better monitoring, differences in business models, and offload of risks to GSEs. A loan-level analysis points towards IT improving borrower screening, while we do not find any evidence in favor of other potential explanations.

References

Acharya, Viral V, Philipp Schnabl, and Gustavo Suarez, "Securitization without risk transfer," *Journal of Financial Economics*, 2013, *107* (3), 515–536.

Adelino, Manuel, Antoinette Schoar, and Felipe Severino, "Loan originations and defaults in the mortgage crisis: The role of the middle class," *The Review of Financial Studies*, 2016, *29* (7), 1635–1670.

Agarwal, Sumit, Gene Amromin, Itzhak Ben-David, Souphala Chomsisengphet, Tomasz Piskorski, and Amit Seru, "Policy intervention in debt renegotiation: Evidence from the home affordable modification program," *Journal of Political Economy*, 2017, *125* (3), 654–712.

Ahnert, Toni, Sebastian Doerr, Nicola Pierri, and Yannick Timmer, "Does IT help? Information technology in banking and entrepreneurship," *IMF Working Papers*, 2021, *2021* (214).

Altonji, Joseph G, Todd E Elder, and Christopher R Taber, "Selection on observed and unobserved variables: Assessing the effectiveness of Catholic schools," *Journal of Political Economy*, 2005, *113* (1), 151–184.

Andrews, Donald WK, Marcelo J Moreira, and James H Stock, "Optimal two-sided invariant similar tests for instrumental variables regression," *Econometrica*, 2006, *74* (3), 715–752.

Andrews, Isaiah and James H Stock, "Weak instruments and what to do about them," *(NBER Summer Institute 2018-Methods Lectures)*, 2018.

Andrews, Michael J, "Local Effects of Land Grant Colleges on Agricultural Innovation and Output," *NBER workin paper*, 2019.

Atkin, David, Azam Chaudhry, Shamyla Chaudry, Amit K Khandelwal, and Eric Verhoogen, "Organizational barriers to technology adoption: Evidence from soccer-ball producers in Pakistan," *The Quarterly Journal of Economics*, 2017, *132* (3), 1101–1164.

Beaudry, Paul, Mark Doms, and Ethan Lewis, "Should the personal computer be considered a technological revolution? Evidence from US metropolitan areas," *Journal of Political Economy*, 2010, *118* (5), 988–1036.

Beccalli, Elena, "Does IT investment improve bank performance? Evidence from Europe," *Journal of Banking & Finance*, 2007, *31* (7), 2205–2230.

Becker, Gary S, *Human capital: A theoretical and empirical analysis, with special reference to education*, University of Chicago press, 2009.

Benmelech, Efraim and Carola Frydman, "Military ceos," *Journal of Financial Economics*, 2015, *117* (1), 43–59.

Berg, Tobias, "Playing the devil's advocate: The causal effect of risk management on loan quality," *The Review of Financial Studies*, 2015, *28* (12), 3367–3406.

__ , Manju Puri, and Jorg Rocholl, "Loan Officer Incentives, Internal Rating Models and Default Rates," *Review of Finance*, 2020.

__ , Valentin Burg, Ana Gombović, and Manju Puri, "On the rise of FinTechs–Credit scoring using digital footprints," *The Review of Financial Studies*, 2019.

Berger, Allen N, "The economic effects of technological progress: Evidence from the banking industry," *Journal of Money, Credit and Banking*, 2003, pp. 141–176.

Bertrand, M and A Schoar, "The Managing with Style: The Effect of Managers on Corporate Policy," *Quarterly Journal of Economics*, 2003, *118* (4), 1169.

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan, "How much should we trust differences-in-differences estimates?," *The Quarterly journal of economics*, 2004, *119* (1), 249–275.

Bloom, Nicholas, Benn Eifert, Aprajit Mahajan, David McKenzie, and John Roberts, "Does management matter? Evidence from India," *The Quarterly Journal of Economics*, 2013, *128* (1), 1–51.

—, Raffaella Sadun, and John Van Reenen, "Americans do IT better: US multinationals and the productivity miracle," *American Economic Review*, 2012, *102* (1), 167–201.

Blythe, LeGette and Charles Raven Brockmann, *Hornets' Nest: The Story of Charlotte and Mecklenburg County*, Public Library of Charlotte and Mecklenburg County, 1961.

Bofondi, Marcello and Francesca Lotti, "Innovation in the retail banking industry: the diffusion of credit scoring," *Review of Industrial Organization*, 2006, *28* (4), 343–358.

Boot, Arnoud, Peter Hoffmann, Luc Laeven, and Lev Ratnovski, "Fintech: what's old, what's new?," *Journal of Financial Stability*, 2021, *53*, 100836.

Bostandzic, Denefa and Gregor NF Weiss, "Innovating Banks and Local Lending," *Available at SSRN 3421123*, 2019.

Branzoli, Nicola, Edoardo Rainone, and Ilaria Supino, "The Role of Banks' Technology Adoption in Credit Markets during the Pandemic," *Available at SSRN 3878254*, 2021.

Bresnahan, Timothy F, Erik Brynjolfsson, and Lorin M Hitt, "Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence," *The Quarterly Journal of Economics*, 2002, *117* (1), 339–376.

Brynjolfsson, Erik and Lorin M Hitt, "Computing productivity: Firm-level evidence," *Review of Economics and Statistics*, 2003, *85* (4), 793–808.

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru, "Fintech, regulatory arbitrage, and the rise of shadow banks," *Journal of Financial Economics*, 2018, *130* (3), 453–483.

Caballero, Ricardo J, Takeo Hoshi, and Anil K Kashyap, "Zombie lending and depressed restructuring in Japan," *American Economic Review*, 2008, *98* (5), 1943–77.

Carletti, Elena, Stijn Claessens, Antonio Fatás, and Xavier Vives, *Barcelona Report 2-The Bank Business Model in the Post-Covid-19 World*, Centre for Economic Policy Research, 2020.

Claessens, Stijn, Jon Frost, Grant Turner, and Feng Zhu, "Fintech credit markets around the world: size, drivers and policy issues," *BIS Quarterly Review September*, 2018.

Dadoukis, Aristeidis, Maurizio Fiaschetti, and Giulia Fusi, "IT adoption and bank performance during the Covid-19 pandemic," *Economics Letters*, 2021, *204*, 109904.

D'Andrea, Angelo and Nicola Limodio, "High-speed internet, financial technology and banking in africa," *BAFFI CAREFIN Centre Research Paper*, 2019, (2019-124).

Degryse, Hans and Steven Ongena, "Distance, lending relationships, and competition," *The Journal of Finance*, 2005, *60* (1), 231–266.

Demirgüç-Kunt, Asli and Enrica Detragiache, "Does deposit insurance increase banking system stability? An empirical investigation," *Journal of Monetary Economics*, 2002, *49* (7), 1373–1406.

FSB, "FinTech and market structure in financial services: Market developments and potential financial stability implications," *Basel: Financial Stability Board*, 2019.

Fuster, Andreas, Matthew Plosser, Philipp Schnabl, and James Vickery, "The role of technology in mortgage lending," *The Review of Financial Studies*, 2019, *32* (5), 1854–1899.

__ , Paul Goldsmith-Pinkham, Tarun Ramadorai, and Ansgar Walther, "Predictably unequal? the effects of machine learning on credit markets," *Journal of Finance*, 2018.

Hannan, Timothy H and John M McDowell, "The determinants of technology adoption: The case of the banking firm," *The RAND Journal of Economics*, 1984, pp. 328–335.

__ and __ , "Rival precedence and the dynamics of technology adoption: an empirical analysis," *Economica*, 1987, pp. 155–171.

He, Zhiguo, Sheila Jiang, Douglas Xu, and Xiao Yin, "Investing in Lending Technology: IT Spending in Banking," *University of Chicago, Becker Friedman Institute for Economics Working Paper*, 2021, (2021-116).

Hernández-Murillo, Rubén, Gerard Llobet, and Roberto Fuentes, "Strategic online banking adoption," *Journal of Banking & Finance*, 2010, *34* (7), 1650–1663.

Hirtle, Beverly, Anna Kovner, and Matthew C Plosser, "The impact of supervision on bank performance," *FRB of NY Staff Report*, 2018.

Hurst, Erik, Benjamin J Keys, Amit Seru, and Joseph Vavra, "Regional redistribution through the US mortgage market," *American Economic Review*, 2016, *106* (10), 2982–3028.

Keller, Wolfgang, "Geographic localization of international technology diffusion," *American Economic Review*, 2002, *92* (1), 120–142.

Keys, Benjamin J, Amit Seru, and Vikrant Vig, "Lender screening and the role of securitization: evidence from prime and subprime mortgage markets," *The Review of Financial Studies*, 2012, *25* (7), 2071–2108.

__ , Tanmoy Mukherjee, Amit Seru, and Vikrant Vig, "Financial regulation and securitization: Evidence from subprime loans," *Journal of Monetary Economics*, 2009, *56* (5), 700–720.

__ , __ , __ , and __ , "Did securitization lead to lax screening? Evidence from subprime loans," *The Quarterly Journal of Economics*, 2010, *125* (1), 307–362.

Kovner, Anna, James I Vickery, and Lily Zhou, "Do big banks have lower operating costs?," *Economic Policy Review*, 2014, *20* (2), 1–27.

Kwan, Alan, Chen Lin, Vesa Pursiainen, and Mingzhu Tai, "Stress Testing Banks' Digital Capabilities: Evidence From the COVID-19 Pandemic," *mimeo*, 2021.

Lewellen, Stefan and Emily Williams, "Did technology contribute to the housing boom? Evidence from MERS," *Journal of Financial Economics*, 2021.

Liberti, José María and Mitchell A Petersen, "Information: Hard and soft," *Review of Corporate Finance Studies*, 2018, *8* (1), 1–41.

Maggio, Marco Di and Vincent Yao, "Fintech Borrowers: Lax Screening or Cream-Skimming?," *The Review of Financial Studies*, 2021, *34* (10), 4565–4618.

Moreira, Marcelo J, "A conditional likelihood ratio test for structural models," *Econometrica*, 2003, *71* (4), 1027–1048.

Moretti, Enrico, "Estimating the social return to higher education: evidence from longitudinal and repeated cross-sectional data," *Journal of econometrics*, 2004, *121* (1-2), 175–212.

Olea, José Luis Montiel and Carolin Pflueger, "A robust test for weak instruments," *Journal of Business & Economic Statistics*, 2013, *31* (3), 358–369.

Oster, Emily, "Unobservable selection and coefficient stability: Theory and evidence," *Journal of Business & Economic Statistics*, 2019, *37* (2), 187–204.

Peek, Joe and Eric S Rosengren, "Collateral damage: Effects of the Japanese bank crisis on real activity in the United States," *American Economic Review*, 2000, *90* (1), 30–45.

Petersen, Mitchell A and Raghuram G Rajan, "The benefits of lending relationships: Evidence from small business data," *The Journal of Finance*, 1994, *49* (1), 3–37.

— and — , "Does distance still matter? The information revolution in small business lending," *The Journal of Finance*, 2002, *57* (6), 2533–2570.

Pierri, Nicola and Yannick Timmer, "IT Shields: Technology Adoption and Economic Resilience during the COVID-19 Pandemic," *IMF Working Papers*, 2020, *2020* (208).

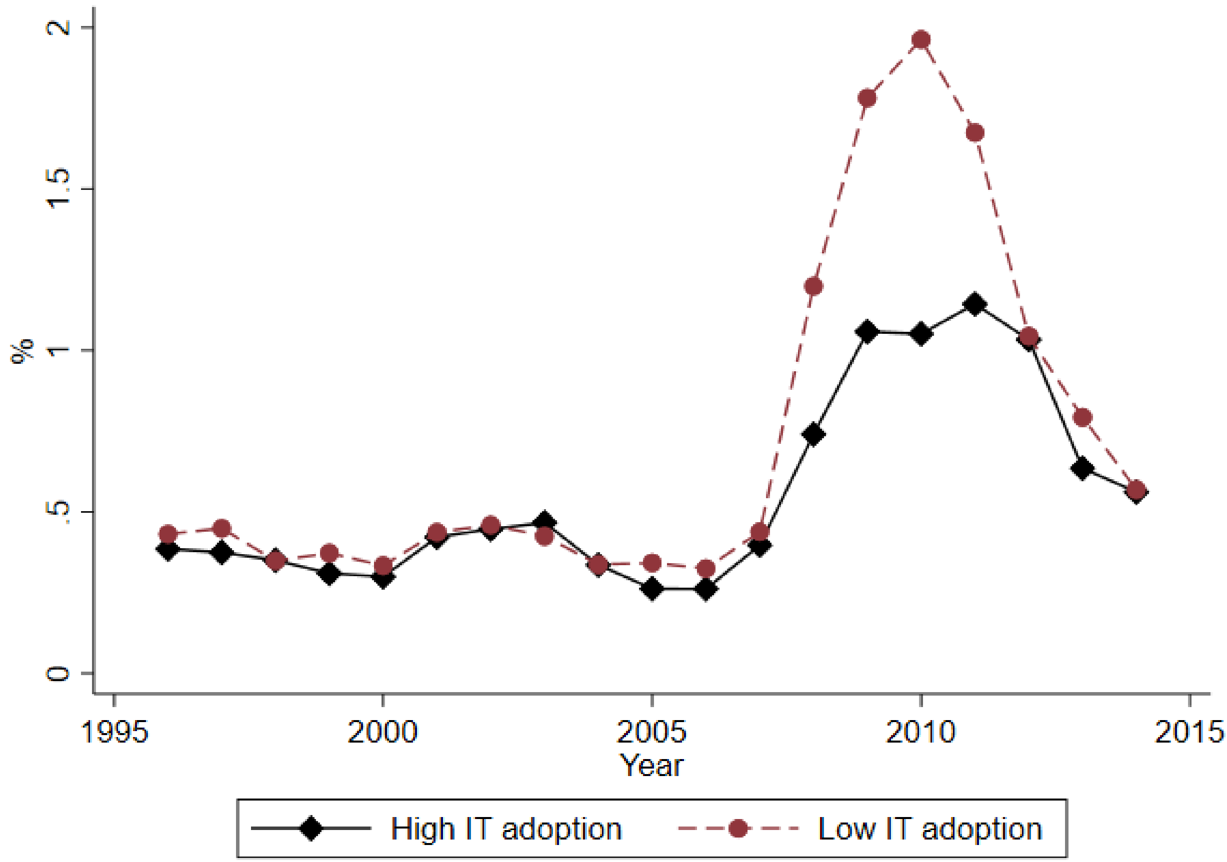
Rajan, Raghuram G, "Has finance made the world riskier?," *European Financial Management*, 2006, *12* (4), 499–533.

Rajan, Uday, Amit Seru, and Vikrant Vig, "The failure of models that predict failure: Distance, incentives, and defaults," *Journal of Financial Economics*, 2015, *115* (2), 237–260.

Santacreu, Ana Maria, "What Drives International Technology Diffusion? A Gravity Approach," *FRB St. Louis Working Paper*, 2019, (2019-31).

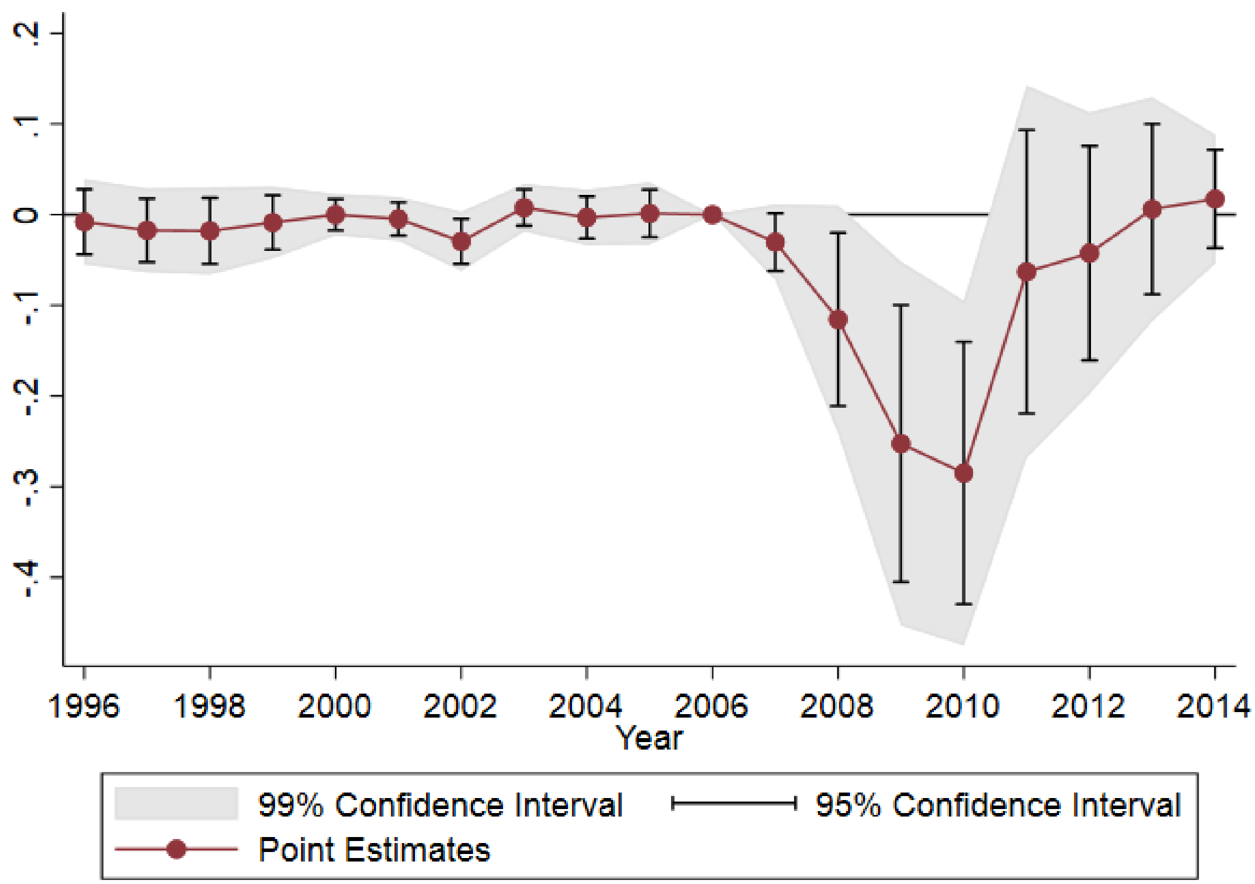
Shapiro, Jesse M, “Smart cities: quality of life, productivity, and the growth effects of human capital,” *The review of economics and statistics*, 2006, *88* (2), 324–335.

Figure 1: NPLs over Assets by pre-GFC IT adoption



This Figure plots the median share of NPLs over assets for high- and low-IT adopters. “High IT adoption" is the median share of NPLs over assets for banks with IT_b above the 75th percentile. “Low-IT adoption" is the median share of NPLs over assets for banks with IT_b below the 25th percentile. We include only banks for which we have regulatory data for at least 14 years. See subsection 3.1 and section 2 for more details.

Figure 2: Time-varying Effect of IT adoption on NPLs

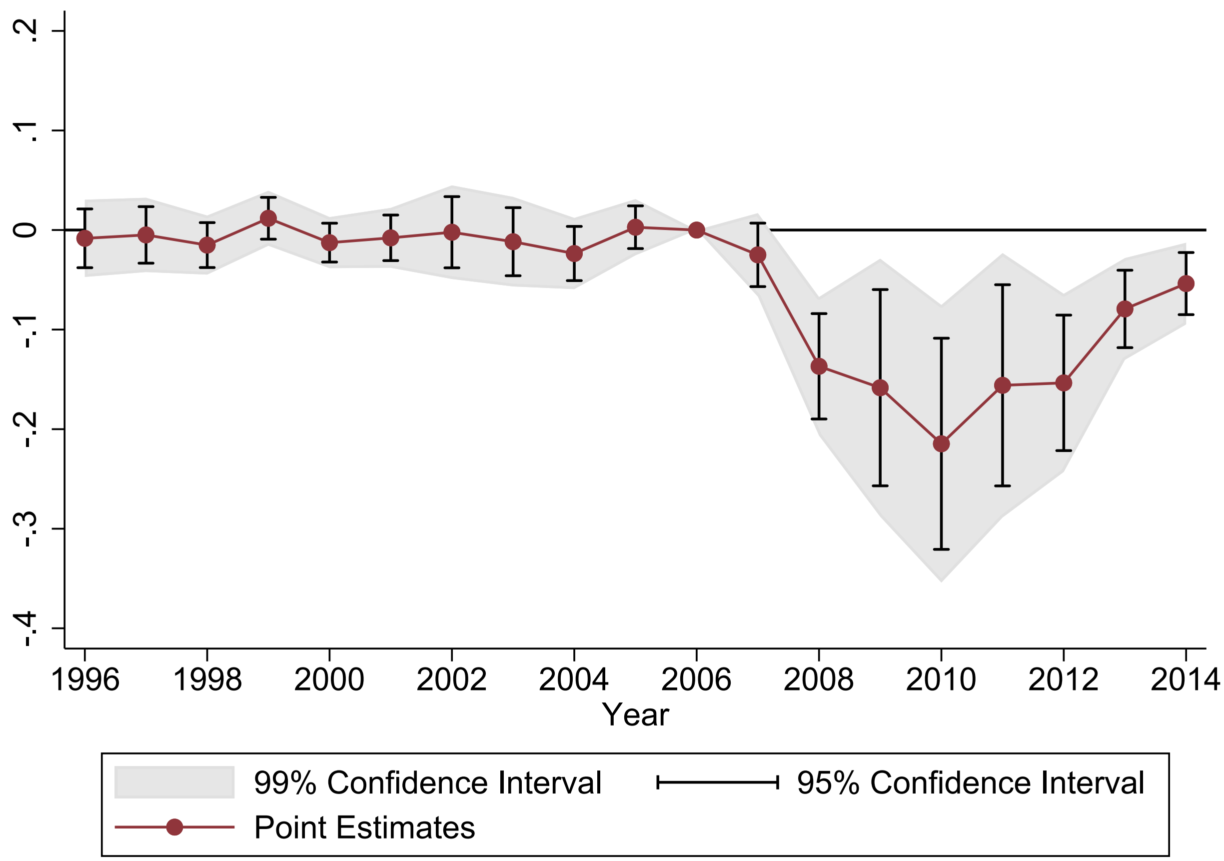


This Figure plots the coefficient and the 95% and 99% confidence intervals of β_τ from the following estimated equation:

$$NPL_{b,t} = \alpha_b + \delta_t + \sum_{\tau \neq 2006} \beta_\tau IT_b \cdot 1[t = \tau] + \epsilon_{b,t}$$

where b is a bank (BHC), t one year between 1996 and 2014, α_b are bank fixed effects, and δ_t are year fixed effects. The dependent variable $NPL_{b,t}$ is the share of NPLs over assets in b's regulatory filing for year t. IT_b is the pre-crisis IT adoption of bank b estimated as described in section 2. The coefficient of 2006 is normalized to zero. Confidence intervals are based on double-clustered standard errors at the bank and year level. See subsection 3.1 and section 2 for more details.

Figure 3: Time-varying Effect of tech-background of executives on NPLs

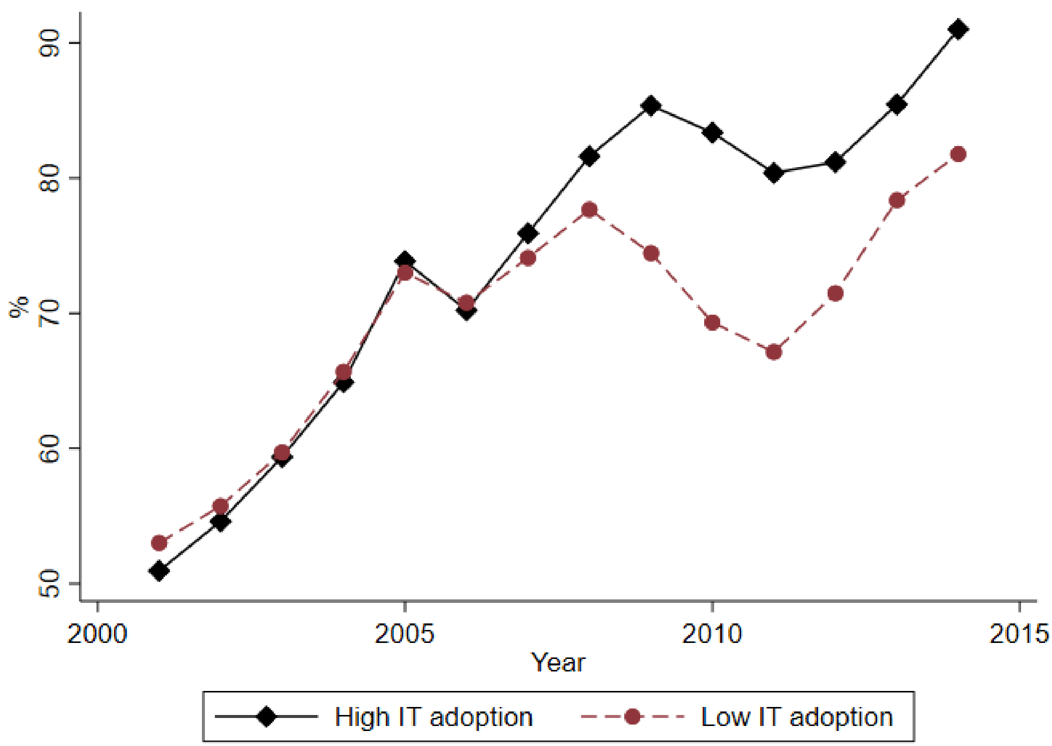


This Figure plots the coefficient and the 95% and 99% confidence intervals of β_τ from the following estimated equation:

$$NPL_{b,t} = \alpha_b + \delta_t + \sum_{\tau \neq 2006} \beta_\tau ExecIT_b \cdot 1[t=\tau] + \epsilon_{b,t}$$

where b is a bank (BHC), t one year between 1996 and 2014, α_b are bank fixed effects, and δ_t are year fixed effects. The dependent variable $NPL_{b,t}$ is the share of NPLs over assets in b's regulatory filing for year t. $ExecIT_b$ is the average "tech-orientation" of bank's b top executives (CEOs, CFOs, and Presidents). The "tech-orientation" of a banks' executives is computed by dividing the total amount of "tech-related" keywords over the total amount of words in their biographies, see subsection 4.1 and section 2 for more details. The coefficient of 2006 is normalized to zero. Confidence intervals are based on double-clustered standard errors at the bank and year level. See subsection 3.1 and section 2 for more details.

Figure 4: Loans over pre-crisis Assets by pre-GFC IT adoption



This Figure plots the median share of total loans scaled by average pre-crisis (2001-2006) assets for high- and low-IT adopters. "High IT adoption" is the median share of Loan over pre-crisis assets for banks with IT_b above the 75th percentile. "Low IT adoption" is the median share of Loan over pre-crisis assets for banks with IT_b below the 25th percentile. We include only banks for which we have regulatory data for at least 14 years. See subsection 3.4 and section 2 for more details.

Table 1: Panel Regressions

	(1)	(2)	(3)	(4)	(5)
	NPL	NPL	NPL	NPL	NPL
IT-adoption	-0.0239		-0.0283		
	(0.017)		(0.018)		
crisis	0.811^{**}	0.793^{**}			
	(0.349)	(0.346)			
IT-adoption × crisis	-0.160^{**}	-0.168^{**}	-0.157^{**}	-0.170^{**}	-0.151^{**}
	(0.063)	(0.065)	(0.066)	(0.068)	(0.067)
IT of local competitors × crisis					0.0309
					(0.044)
(Within) R-squared	0.112	0.140	0.0111	0.00997	0.0482
N	4608	4608	4608	4608	4608
Bank FE	No	Yes	No	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
Bank controls × crisis	No	No	No	No	Yes

Results of estimating the following equation:

$$NPL_{b,t} = \alpha_b + \delta_t + \beta IT_b \cdot crisis + (X_b \cdot crisis_t)'\gamma + \epsilon_{b,t}$$

where b is a bank (BHC), t one year between 2001 and 2014, $crisis_t$ a dummy variable indicating years 2007 to 2010, α_b are bank fixed effects, and δ_t are year fixed effects. The dependent variable $NPL_{b,t}$ is the share of NPLs over assets in b's regulatory filing for year t. IT_b is the pre-crisis IT adoption of bank b estimated as described in section 2. The bank-level set of controls X_b includes the pre-crisis (2001-2006) average of: the loans to assets ratio, the capital to assets ratio, the wholesale funding ratio, ROA, the (log of) average wages in thousands of USD, and the (log of) assets size in thousands of USD. X_b also includes the average IT adoption of local competitors and a measure of exposure to the house price shocks (HP Exposure) based on the combination observed percentage change in prices (2006Q4-2010Q4) in each county and the location of banks' branches. Columns (1) and (3) exclude bank fixed effect, while column (1) and (2) exclude year fixed effects. Column (5) includes interacted controls but only displays the one between IT of local competitors. See subsection 3.1 and section 2 for more details. Sample size is kept constant by dropping observations with missing values for any variable. Standard errors (in parentheses) are double-clustered on bank and year level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Cross-Sectional Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	NPL	Loans	Size	HP Exposure	Capital	Wholesale	ROA	Log Wage	IT of local comp.	NPL
IT-adoption	-0.183***	-0.648	-0.0931	0.131	-0.195	-0.0459	-0.0282	-0.0227	0.275***	-0.168***
	(0.061)	(0.700)	(0.057)	(0.108)	(0.420)	(0.372)	(0.049)	(0.018)	(0.083)	(0.061)
R-squared	0.0262	0.00220	0.00712	0.000875	0.000427	0.0000383	0.00107	0.00414	0.0750	0.186
N	337	337	337	337	337	337	337	337	337	337
Mean	1.54	62.69	13.9	.64	13.02	15.92	2.55	4.84	.01	1.54
Std.Dev.	1.13	13.8	1.1	4.41	9.43	7.41	.86	.35	1	1.13

Results of estimating the following equation:

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

where b is a bank (BHC) and IT_b is the pre-crisis IT adoption of b, estimated as described in section 2. The dependent variable Y_b is either the share of NPLs over assets in bank b regulatory filing (averaged over 2007 to 2010) or one of the variables of the set X_b, defined as follow. X_b includes the pre-crisis (2001-2006) average of: the loans to assets ratio, the capital to assets ratio, the wholesale funding ratio, ROA, the (log of) average wages in thousands of USD, and the (log of) assets size in thousands of USD. X_b also includes the average IT adoption of local competitors and a measure of exposure to the house price shocks (HP Exposure) based on the combination of the observed percentage change in prices (2006Q4-2010Q4) in each county and the location of banks' branches. In column (10) the dependent variable is the share of NPLs over assets and the set of covariates X_b are included as controls. See subsection 3.2 and section 2 for more details. Sample size is kept constant by dropping observations with missing values for any variable. Robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: NPLs by Loan Category

	(1)	(2)	(3)	(4)	(5)	(6)
NPLs during crisis:	Residential RE	Commercial RE	C&I	Residential RE	Commercial RE	C&I
Normalized by	Loans in the category			Total Assets		
IT-adoption	-0.196**	-0.396***	-0.256***	-0.0311**	-0.129**	-0.0253***
	(0.0927)	(0.138)	(0.0878)	(0.0139)	(0.0642)	(0.00946)
R-squared	0.0108	0.0195	0.0279	0.00995	0.0154	0.0243
N	284	285	285	285	285	285
Average NPLs during crisis	2.062	3.469	1.662	0.332	1.062	0.165
Normalized by average NPLs	-0.0949	-0.114	-0.154	-0.0936	-0.121	-0.153

Results of estimating the following equation:

$$Y_b^k = \alpha + \beta IT_b + \epsilon_b$$

where b is a bank (BHC) and IT_b is the pre-crisis IT adoption of b, estimated as described in section 2. The dependent variable Y_b is the share of NPLs in loan category k in bank b regulatory filing (averaged over 2007 to 2010). Column (1) and (4) report the results for residential real estate NPLs, columns (2) and (5) for commercial real estate and (3) and (6) for commercial and industrial loan npls. In columns (1)-(3) we divide by the amount of loans by the bank in the respective category and in columns (4)-(6) we divide by total assets of the bank. b/mean displays the respective coefficient relative to the mean of the y variable. b/sd displays the respective coefficient relative to the standard deviation of the y variable. See subsection 3.2 and section 2 for more details. Robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Executives' "tech-orientation"

	(1)	(2)	(3)	(4)	(5)	(6)
	IT	NPL	NPL	NPL	NPL	NPL
Tech-orientation	0.104*	-0.255***		-0.237***	-0.131**	-0.142*
	(0.057)	(0.069)		(0.068)	(0.065)	(0.073)
Log Compensation			-0.131*	-0.108	-0.0611	-0.00878
			(0.069)	(0.068)	(0.074)	(0.076)
Management					-0.0518	-0.0958
					(0.115)	(0.133)
Post-Grad						0.344
						(0.332)
Long tenure						-0.232
						(0.208)
Female						-0.761*
						(0.440)
Age						0.0239*
						(0.013)
R-squared	0.0136	0.0455	0.0205	0.0592	0.276	0.306
N	149	156	156	156	156	156

Results of estimating the following equation:

$$Y_b = \alpha + \beta ExecIT_b + \epsilon_b$$

where b is a bank (BHC). The dependent variable Y_b is either the ratio of NPLs to assets averaged between 2007 and 2010 (columns (2)-(6)), or the pre-crisis IT adoption (column 1), estimated as described in section 2. The independent variable $ExecIT_b$ is the "tech-orientation" of bank's b top executives (CEOs, CFOs, and Presidents). The "tech-orientation" of a banks' executives is computed by dividing the total amount of "tech-related" keywords over the total amount of words in their biographies, see subsection 4.1 and section 2 for more details. Log Compensation is the log average compensation of the executives. Management is computed by dividing the total amount of "management" keywords over the total amount of words in their biographies. Post-grad is the share of executives with a post-grad degree. Long-tenure is the share of executives with an above median tenure at its current position. Female is the share of female executives. Age is the average age of the executives. Columns (5) and (6) add the set of pre-GFC bank level controls described in section 2. Robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Land-Grant Colleges Instruments

	(1)	(2)	(3)	(4)
	NPL	NPL	NPL	NPL
IT-adoption	-1.343**	-0.859**	-0.877**	-0.850*
	(0.560)	(0.430)	(0.409)	(0.434)
Effective F-stat	3.14	2.42	2.7	3.84
Instruments	3 closest	3 closest	3 closest	2 closest
Controls	No	Yes	Yes	Yes
N	337	337	306	337
Sample	All	All	Excl West	All
	90% Confidence Intervals (Robust to Weak Instruments)			
Wald CI:	[-2.26,-.42]	[-1.57,-.15]	[-1.55,-.20]	[-1.56,-.14]
CLR CI:	[... ,-.50]	[-2.40,-.21]	[-2.21,-.29]	[-2.20,-.21]
K CI:	[... ,-.50]	[-2.07, -.28]	[-2.02,-.34]	[-2.05,-.24]
K-J CI:	[... , -.45]	[-2.21,-.24]	[-2.15,-.30]	[-2.20,-.21]
	95% Confidence Intervals (Robust to Weak Instruments)			
Wald CI:	[-2.44, -.25]	[-1.70,-.02]	[-1.68,-.08]	[-1.70, .00]
CLR CI:	[... ,-.34]	[-3.51,-.03]	[-2.94,-.15]	[-2.96,-.06]
K CI:	[... ,-.36]	[-2.63,-.16]	[-2.50, -.21]	[-2.62,-.11]
K-J CI:	[... ,-.31]	[-2.85,-.11]	[-2.69,-.18]	[-2.85,-.08]

Results of estimating the following 2SLS equation:

$$IT_b = \delta + \sum_j \rho_j \cdot D_{b(c),j} + \eta_b$$

$$NPL_b = \alpha + \beta \cdot IT_b + \epsilon_b$$

where b is a bank (BHC). NPL_b is the ratio of NPLs to assets averaged between 2007 and 2010. IT_b is pre-crisis IT adoption, estimated as described in section 2. $D_{b(c),j}$ is the distance in log miles (plus one) between the county of land-grant college j and BHC b's headquarter county, weighted by the log size of the college. We also include–in both first and second stage–a set of pre-crisis BHC-level controls plus a set of county-level controls for headquarter county. Effective first stage F-stats from Olea and Pflueger (2013) are displayed. The bottom panels report the 90% and 95% weak-instrument confidence intervals constructed with different statistics (Andrews and Stock, 2018). The ... in column (1) indicate there is no estimated lower bound to those confidence intervals. To search for a lower bound, we expand the grid up to an "unreasonably low" value for the impact of IT on NPLs: the value such that a one standard deviation higher IT adoption would be predicted to offset all the NPLs for 99% of BHC (i.e., -4.71); such value cannot be rejected for the specification with no controls (column 1). leaving the lower bounds undefined. Column (3) exclude BHC headquartered on the West Coast (Alaska, California, Oregon, Washington), Hawaii, or Puerto Rico. See subsection 4.2 for more details. Robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Loan-Level Regressions

	Ever Deliquent 90 Days +				Modified	Credit Score
	(1)	(2)	(3)	(4)	(5)	(6)
IT adoption - originator	-0.118*		-0.302***	-0.325***		-0.601
	(0.059)		(0.080)	(0.069)		(0.587)
IT adoption × High Credit Score		0.0327				
		(0.109)				
IT adoption × Low Credit Score		-0.271**				
		(0.113)				
IT adoption - servicer				0.337	-1.502	
				(0.509)	(0.932)	
Origination	2004/2006	2004/2006	2000/2006	2004/2006	2004/2006	2004/2006
R2	0.0889	0.0890	0.0765	0.0871	0.103	0.115
Observations	5,063,032	5,063,032	16,406,595	4,387,965	303,809	5,063,032

Results of estimating the following equation:

$$Delinquent_l = \alpha_{z(l),o(l)} + \beta IT_{b(l)} + X_l'\gamma + \eta_l$$

where l is a mortgage held by Freddie Mac or Fannie Mae and originated before 2007, $\alpha_{z(l),o(l)}$ are postal-code$*$origination-year fixed effects of the underlying loan. $IT_{b(l)}$ is the is the pre-crisis IT adoption of the bank which sold the mortgage to Freddie Mac or Fannie Mae, estimated as described in section 2. The dependent variable $Delinquent_l$ is a dummy variable indicating whether a loan was ever delinquent for 90+ days (multiplied by 100) anytime up to 2010. $\alpha_{z(l),o(l)}$ are origination zipcode × year fixed effects, while the vector of controls X_l includes the credit score score, the debt servicing to Income (DTI), the Loan-to-Value (LTV) ratios at origination, the occupancy status, the loan purpose, a dummy for a loan with multiple borrowers, the log loan amount, and the origination channel. All independent variables are standardized to have a mean of 0 and a standard deviation of 1. Column (2) interacts banks' IT adoption with a dummy variable indicating whether the borrower has a Credit Score above or below the median. Column (3) includes mortgages originated since 2000, so to expand the sample of origination banks: 28 versus 18 for columns (1)-(2). Column (4) adds the IT adoption of the servicing firm. Column (5) replaces the dependent variable with a dummy if the loan has ever been modified. It includes only loans that have been delinquent at least once. Column (6) replaces the dependent variable with the credit score of the borrower. See section 5 and section 2 for more details. Standard errors (in parentheses) are cluster at the origination bank-level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Supplemental Materials

A1 Land-Grant Colleges Characteristics and Headquarter Selection

In this section we study the characteristics of land-grant colleges' students and how the location of land-grant colleges impact banks' headquarters location. These results are complementary to the analysis in subsection 4.2. The IPEDS survey provides data on the major and SAT scores for students enrolled in more than 1,400 higher education institutions in the US during fall 2018. We then estimate the following regressions:

$$Share_{u,M} = \alpha_M + \beta_M Landgrant_u + \epsilon_{u,M}$$

and

$$SAT\_Score_u = \alpha + \beta Landgrant_u + \epsilon_u$$

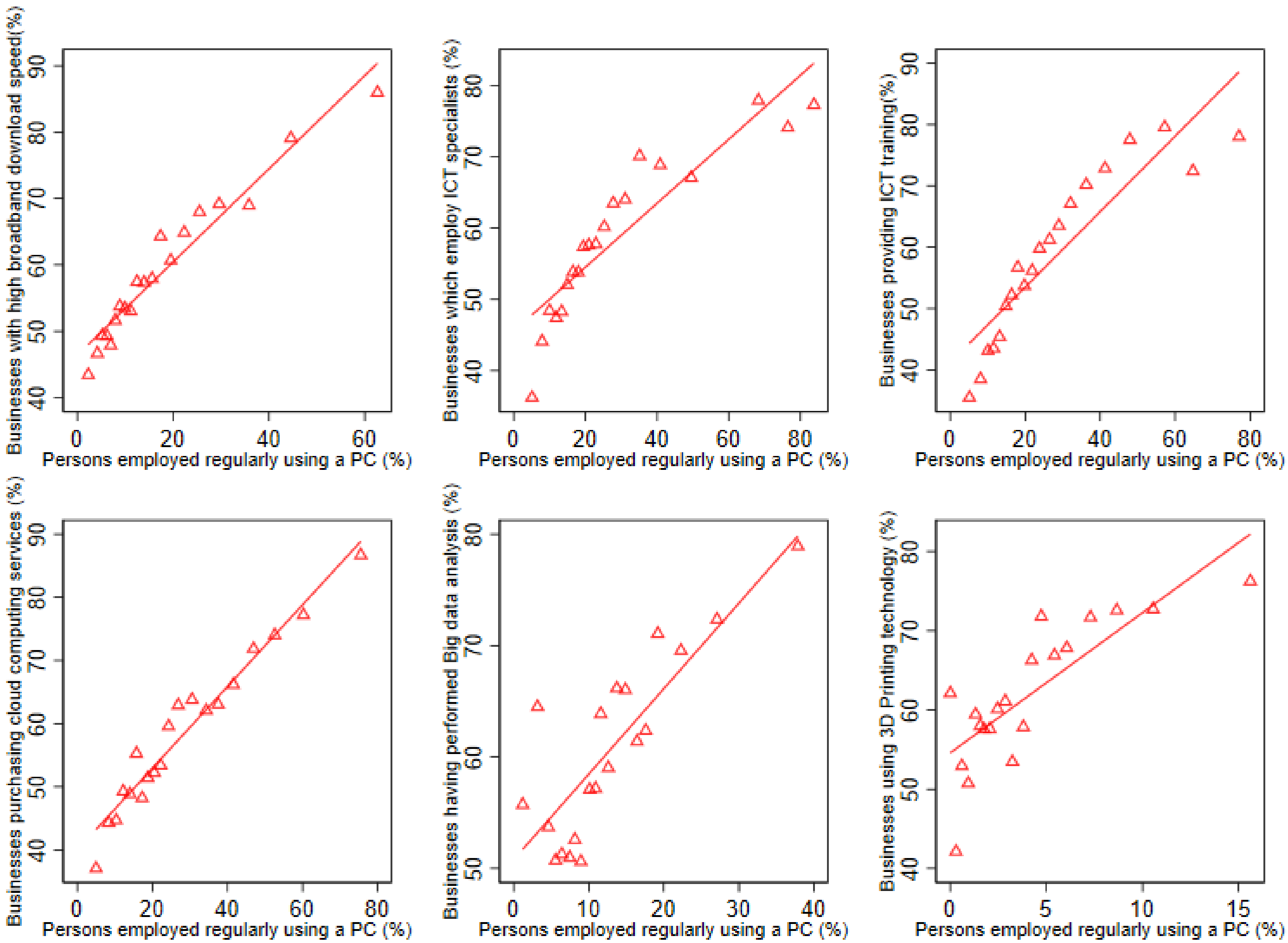
where $Share_{u,M}$ is the share of students in each of 6 fields of study M we have information on (we drop dentistry school) in institution u, SAT_Score_u is the 25th or 75th percentile of SAT score in reading or math of the enrolled students, and $Landgrant_u$ is a dummy flagging whether u is a land-grant college or university. Results are reported in Table A3 and Table A4. Land-grant institutions have a much larger share of students enrolled in engineering and slightly more students in other scientific disciplines, such as biology and physics. Conversely, they have much fewer students in business and management science and also less students in education. Moreover, students at land-grant colleges have significantly higher math scores (whether we look at the 25th or 75th percentile) but similar reading scores. These results indicate that land-grant colleges are mainly technical schools. We repeat the analysis using data from fall 1996 (since we take bank headquarter location in 1995 when possible) and find very similar results.

We then move to analyze whether the distance from land-grant colleges predicts headquarters' location. We estimate the following linear probability model:

$$BankHQ_c = \alpha + \beta Distance\_Landgrant_c + \gamma X_c + \epsilon_c$$

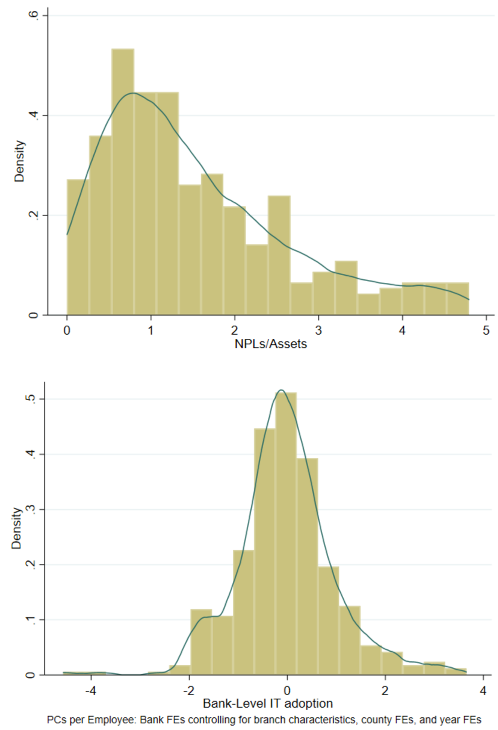
where $BankHQ_c$ is a dummy variable indicating whether the county c host the headquarter of one of the 337 BHC of our main sample, and X_c is set of controls including pre-GFC education , income, and state fixed effects. $Distance\_Landgrant_c$ is one of four measure of distance (in log of miles plus one) of county c to land-grant colleges. The first three measures are closest college, median across all colleges, mean across all colleges. The fourth measure is, instead, a linear combination of the distance of the county from all land-grant colleges. The parameters of such linear combination are chosen in a previous estimation stage where we rely on LASSO to predict the IT adoption of a BHC with the distance of the BHC's headquarter from all land-grant colleges. This fourth measure is salient as LASSO extract the variation in the county-colleges distances vector that is more important to explain our variable of interest, that is BHC's IT adoption. Results are presented in Table A5. No measure has statistically significant predictive power. The results are robust to estimating a probit model rather than a linear probability model (unreported).

Figure A1: PC usage and other IT Measures



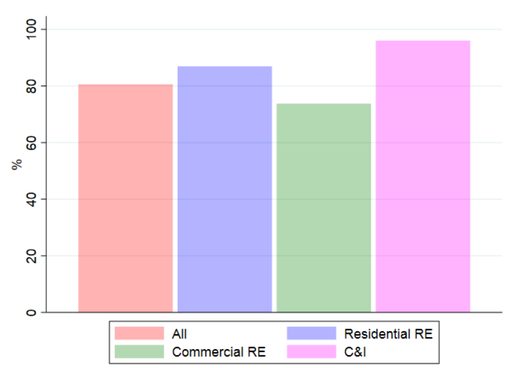
The Figure plots binscatterplots between the various IT measures and the share of employees using a PC using country-class data from the OECD ICT Access and Usage Businesses dataset for 2018, where a class is defined by industry or firm size. Pairwise linear correlations range between 31% and 64%. Same patterns emerge by selecting a different year or pooling data across all years. We thank Francesco Manaresi for suggesting this exercise.

Figure A2: Cross-sectional distribution of NPLs over Assets (crisis) and IT adoption (pre-crisis)



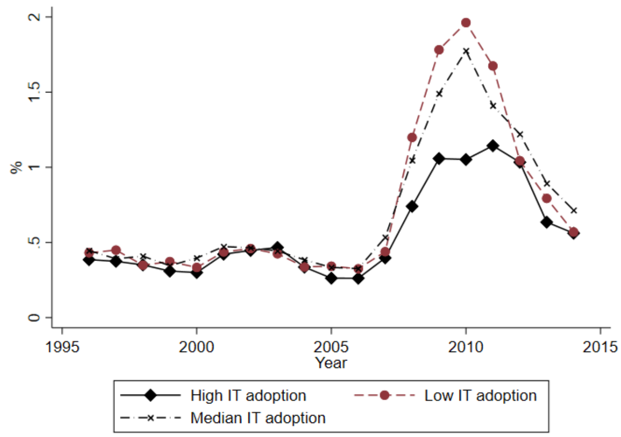
This Figure plots the cross-sectional distribution of the ratio of NPLs to assets averaged between 2007 and 2010 (top panel) and of the pre-crisis IT adoption IT_b. See section 2 for more details.

Figure A3: Coverage by loan type



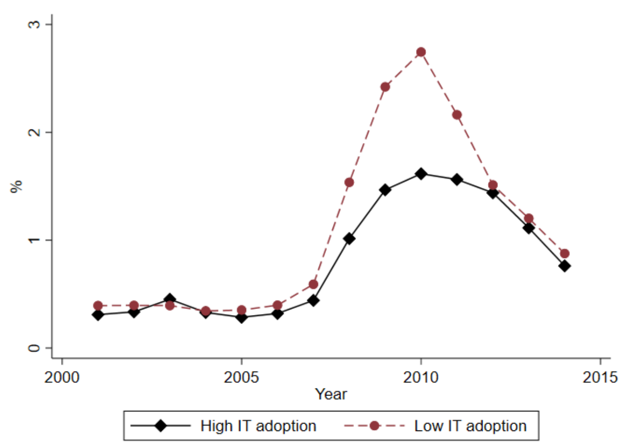
Ratio of loans held by BHC in the matched analysis sample versus total loans in the regulatory dataset, by type of loans (in 2006).

Figure A4: NPLs over Assets by pre-GFC IT adoption



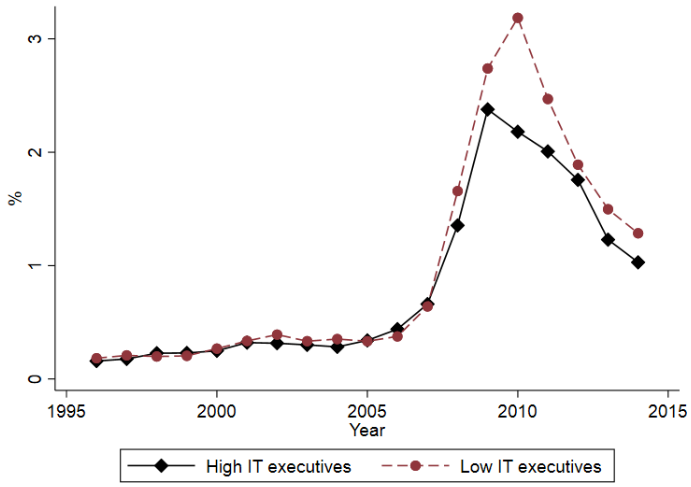
This Figure plots the median share of NPLs over assets for high, medium, and low-IT adopters. “High IT adoption" is the median share of NPLs over assets for banks with IT_b above the 75th percentile. “Low IT adoption" is the median share of NPLs over assets for banks with IT_b below the 25th percentile. “Median IT adoption" is the median share of NPLs over assets for banks with IT_b between the 25th percentile and the 75th percentile. We include only banks for which we have regulatory data for at least 14 years. See subsection 3.1 and section 2 for more details.

Figure A5: NPLs over pre-GFC Assets by pre-GFC IT adoption



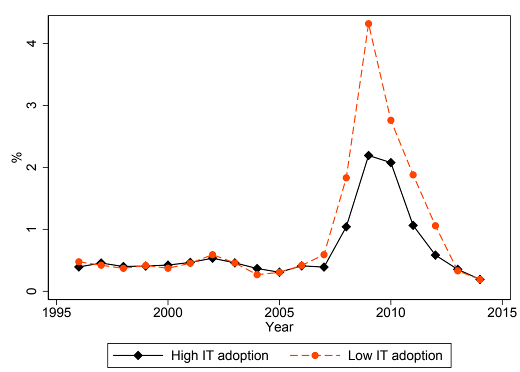
This Figure plots the median share of NPLs scaled by average pre-crisis (2001-2006) assets for high- and low-IT adopters. “High IT adoption" is the median share of NPLs over pre-crisis assets for banks with IT_b above the 75th percentile. “Low-IT adoption" is the median share of NPLs over pre-crisis assets for banks with IT_b below the 25th percentile. We include only banks for which we have regulatory data for at least 14 years. See subsection 3.1 and section 2 for more details.

Figure A6: NPLs over pre-GFC Assets by bank top executives' technology orientation



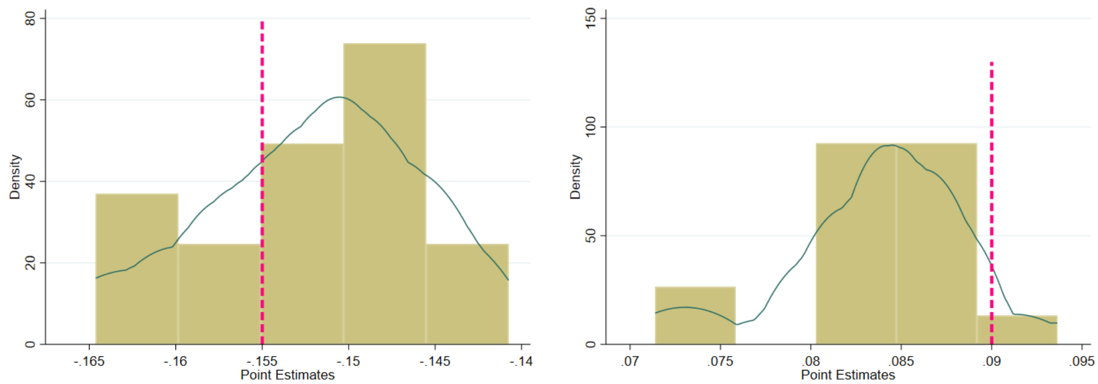
This Figure plots the median share of NPLs scaled by average pre-crisis (2001-2006) assets for banks with high and low executives' "tech-orientation". "High-IT executive" is the median share of NPLs over pre-crisis assets for banks with executives "tech-orientation" above the 75th percentile. "Low-IT executive" is the median share of NPLs over pre-crisis assets for banks with executives "tech-orientation" at or below the 25th percentile. We include only banks for which we have regulatory data for at least 14 years. The "tech-orientation" of banks' executives is computed by dividing the total amount of "tech-related" keywords over the total amount of words in their biographies. We then compute a bank-level measure by averaging over the top executives (CEOs, CFOs, COOs, and Presidents) hired before 2007. See subsection 4.1 and section 2 for more details.

Figure A7: Provision for credit losses over Assets



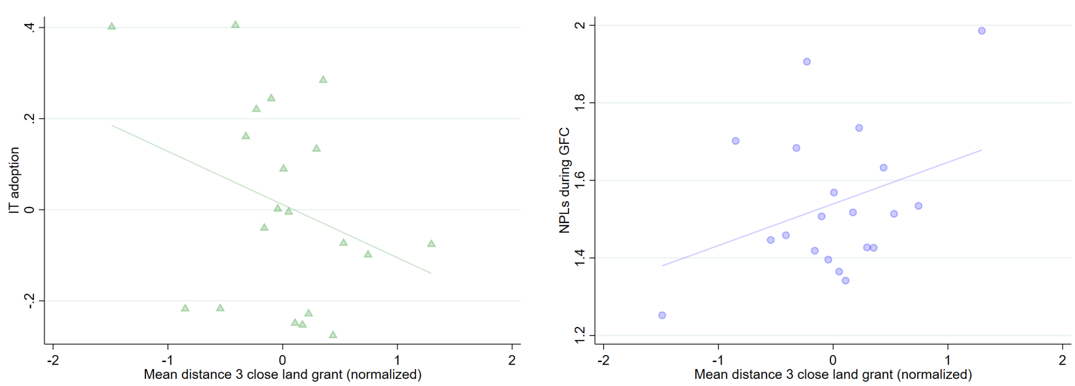
This Figure plots the median share of provision for credit losses scaled by assets high- and low-IT adopters. "High IT adoption" is the median share of NPLs over pre-crisis assets for banks with IT_b above the 75th percentile. "Low-IT adoption" is the median share of NPLs over pre-crisis assets for banks with IT_b below the 25th percentile. We include only banks for which we have regulatory data for at least 14 years. See subsection 3.1 and section 2 for more details.

Figure A8: Robustness of the Executives' results to changes in the keywords list



This Figure plots the coefficient of columns (2)-(3) of Table 4 for different measures of bank top executives' technology orientation. For each word used in defining the technology orientation of executives, we create a new measure in which we leave out this particular word and build the measure based on all remaining words. The dashed line reflect the estimates of columns (2) and (3) of Table 4. See subsection 4.1 and section 2 for more details.

Figure A9: Average distance to nearby land-grant colleges, IT adoption, and NPLs during GFC



The figure plots the average IT adoption and NPLs during GFC for each of 20 bins defined according to the average log distance from the three closest land-grant colleges (weighted by size). All variables are residualized after controlling for BHC pre-crisis characteristics, BHC's headquarter county characteristics, and state fixed effects. The distance is normalized to to have mean zero and unit standard deviation.

Table A1: Robustness of Main Panel Regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	NPL	NPL	NPL	NPL	NPL	NPL	NPL	NPL	NPL	NPL
IT-adoption × crisis	-0.165**	-0.243*	-0.158**	-0.161**	-0.242**	-0.214**	-0.380*	-0.882**	-0.165***	-0.165***
	(0.068)	(0.120)	(0.069)	(0.063)	(0.095)	(0.080)	(0.183)	(0.404)	(0.051)	(0.054)
Exercise	Baseline	PCs per Emp	HW IT	HW NPLs	Loans	Broad def.	As of 2006	Provisions	Bank Clustering	Bootstrapped s.e.
R-squared	0.00944	0.00376	0.00794	0.0108	0.00867	0.00993	0.00530	0.00158	0.00944	
N	4692	5035	4692	4692	4692	4692	4655	4548	4692	4692

Results of estimating the following equation:

$$NPL_{b,t} = \alpha_b + \delta_t + \beta IT_b \cdot crisis + \epsilon_{b,t}$$

where b is a bank (BHC), t one year between 2001 and 2014, $crisis_t$ a dummy variable indicating years 2007 to 2010, α_b are bank fixed effects, and δ_t are year fixed effects. The dependent variable $NPL_{b,t}$ is the share of NPLs over assets in b's regulatory filing for year t. IT_b is the pre-crisis IT adoption of bank b estimated as described in section 2. In column (2) the IT adoption is measured by the average PCs per employee in bank b's branches. In column (3) the IT adoption measure is winsorized after estimation at 5 percent on each side. In column (4) the NPLs are winsorized at 5 percent on each side. In column (5) NPLs are normalized by the amount of loans rather than assets. In column (6) NPLs are defined according to a broader definition, which includes loans with shorter delinquency period. In column (7) we normalized NPLs by the average amount of assets that each bank had in the pre-crisis period (2001 to 2006) rather than contemporaneous assets. In column (8) the left hand side are the provision for credit losses over total assets. In column (9) we cluster standard errors only on the bank-level. In column (10) we report bootstrap standard errors based on 500 simulations. (With each random sample, we first re-estimate the first stage–Equation 1–to obtain a new estimate of bank-level IT adoption, and then we estimate the equation of interest. Standard errors are then calculated as the standard deviation of the bootstrap coefficients of interests.) Standard errors (in parentheses) are double-clustered on bank and year level for columns (1)-(7). See subsection 3.1 and section 2 for more details. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Lending Regressions

	(1)	(2)
	Δ Lending	Δ Lending
NPL post-crisis	-0.951***	
	(0.161)	
IT-adoption		0.364*
		(0.187)
R-squared	0.100	0.0115
N	336	336

Results of estimating the following equation:

$$\overline{\Delta Loans}_b^{GFC} = \alpha + \beta X_b + \epsilon_b$$

where b is a bank (BHC). The dependent variable $\Delta Loans_b^{GFC}$ is the loan growth over assets in bank b regulatory filing (averaged over 2007 to 2010). X_b is either IT_b is the pre-crisis IT adoption of b, estimated as described in section 2 or the share of NPLs over assets in bank b regulatory filing (averaged over 2007 to 2010). See subsection 4.1 and section 2 for more details. Robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Enrollment by Major

	Share of Enrollment by Major					
	Biology	Business	Education	Engineering	Medicine	Physics
	(1)	(2)	(3)	(4)	(5)	(6)
Landgrant	0.0167*	-0.124***	-0.0892***	0.191***	-0.00226	0.00730**
	(0.009)	(0.012)	(0.013)	(0.017)	(0.002)	(0.003)
R-squared	0.000726	0.0154	0.0100	0.0660	0.000103	0.000720
N	1,468	1,468	1,468	1,468	1,468	1,468

Results of estimating the following equation:

$$Share_{u,M} = \alpha_M + \beta_M Landgrant_u + \epsilon_{u,M}$$

where u is an higher-education institution, and M is a major of study. The dependent variable $Share_{u,M}$ is the ratio of enrollment in major M to enrollment in all degrees in Fall 2018. The independent variable $Landgrant_u$ is a dummy variable that takes the value one if the institution is a land-grant college and zero otherwise. Robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4: SAT Score

	SAT Score Reading		SAT Score Math	
	25th percentile	75th percentile score	25th percentile	75th percentile
	(1)	(2)	(3)	(4)
Landgrant	10.19	10.31	21.61**	25.35**
	(8.652)	(9.922)	(10.922)	(11.650)
R-squared	0.00116	0.00112	0.00461	0.00644
N	1,144	1,144	1,144	1,144

Results of estimating the following equation:

$$SAT\_Score_u = \alpha + \beta Landgrant_u + \epsilon_u$$

where u is a higher-education institution. The dependent variable SAT_Score_u is entry SAT score for either math or reading for the 75th or 25th percentile. The independent variable $Landgrant_u$ is a dummy variable that takes the value one if the university is a land-grant college and zero otherwise. Robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Bank Headquarter Location

	(1)	(2)	(3)	(4)
	Dependent Variable: HQ of Bank			
Average distance from land-grant colleges	-0.0291			
	(0.066)			
Median distance from land-grant colleges		0.0178		
		(0.063)		
Distance from closest land-grant college			-0.00691	
			(0.006)	
LASSO land-grant college IV				0.159
				(0.115)
Education	0.326***	0.323***	0.306***	0.328***
	(0.075)	(0.075)	(0.077)	(0.075)
Income	0.0627***	0.0632***	0.0625***	0.0623***
	(0.005)	(0.005)	(0.005)	(0.005)
R-squared	0.146	0.146	0.147	0.147
N	3144	3144	3144	3144

Results of estimating the following equation:

$$BankHQ_c = \alpha + \beta Distance\_Landgrant_c + \epsilon_c$$

where c is a county. The dependent variable $BankHQ_c$ is a dummy that equals one if one of the BHC of our main sample has its headquarter in the county and zero otherwise. $Distance\_Landgrant_c$ is either the average distance to all land-grant colleges (column 1), the median distance to all land-grant colleges (column (2), the distance to the closest land-grant colleges (column 3), or the LASSO land-grant college IV as described in subsection 4.2 and Table 5 in (column 4). We include a set of county level controls" the share of people with bachelor degrees, the log average household income, and state fixed effects. Robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$