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Tech in Fin before FinTech:
Blessing or Curse for Financial Stability?

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I N T E R N A T I O N A L M O N E T A R Y F U N D

Tech in Fin before FinTech: Blessing or Curse for Financial Stability?*

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Abstract

Motivated by the world-wide surge of FinTech lending, we analyze the implications of lenders' information technology adoption for financial stability. We estimate bank-level intensity of IT adoption before the global financial crisis using a novel dataset that provides information on hardware used in US commercial bank branches after mapping them to their parent bank. We find that higher intensity of IT-adoption led to significantly lower non-performing loans when the crisis hit: banks with a one standard deviation higher IT-adoption experienced 10% lower non-performing loans. High-IT-adoption banks were not less exposed to the crisis through their geographical footprint, business model, funding sources, or other observable characteristics. Loan-level analysis indicates that high-IT-adoption banks originated mortgages with better performance and did not offload low-quality loans. We apply a simple text-analysis algorithm to the biographies of top executives and find that banks led by more “tech-oriented” managers adopted IT more intensively and experienced lower non-performing loans during the crisis. Our results suggest that technology adoption in lending can enhance financial stability through the production of more resilient loans.

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

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

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1 Introduction

The emergence of FinTech has triggered a debate on the effect of Information Technology (IT) on financial stability (FSB, 2019; Claessens et al., 2018; Nasiripour, 2019). The recent literature on FinTech has mostly focused on how the latest technological developments have been changing the way information is processed and the relative consequences for credit allocation and performance; for instance, see Berg et al. (2019b); Buchak et al. (2018); Di Maggio and Yao (2018); Fuster et al. (2019). However, predictive systems which are accurate in good times may fail to predict default in the event of an adverse systemic shock (Rajan et al., 2015, 2010). Since the era of FinTech has not been exposed yet to large shocks testing its resilience, the empirical evidence cannot be conclusive about whether a more IT-driven financial system enhances or endangers financial stability in the medium- and long-run.¹

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 Great 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 experienced a significantly smaller increase in NPLs during the crisis. 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, we do not detect a significant correlation between pre-crisis IT adoption of banks and their non-performing loans outside the crisis. However, once the crisis hit, a one standard deviation increase in IT adoption could have lowered by 15% the surge in NPLs with respect to pre-crisis levels. The non-result in normal times reinforces the argument that it is important to study the effects of IT adoption when the economy faces a system-wide shock.

Bank-level pre-crisis technology adoption may be correlated with other characteristics which impact non-performing loans during the crisis. We find that IT-adoption 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, employees’ wages, and other balance sheet characteristics. The absence of a correlation between IT adoption and these observable characteristics is an

¹Some papers explicitly recognize this limitation. For instance, Hughes et al. (2019) study the performance of personal loans made by a peer-to-peer lending platform (Lending Club) and write in their abstract: “caveat: we note that [...] the results may not hold under different economic conditions such as a downturn.”

useful falsification test: it suggests that our measure is unlikely to be correlated with other unobservable predictors of exposure to the crisis. Furthermore, the estimated impact of IT on NPLs is unaffected by the inclusion of these 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. We also show that banks led by more IT-savvy executives adopted more IT and had fewer NPLs during the crisis, even after controlling for their human capital. This collection of results point towards IT itself as the cause of lower NPLs and against a spurious correlation between the two variables.

Our 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 branch² as the relevant measure of branch-level IT-adoption. We confirm that there is a strong correlation between the share of PCs per employee and the IT budget in 2016, which is likely understating the correlation in the pre-crisis period.³ We then map the bank branches to Bank Holding Companies (BHCs) and estimate a bank 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 bank fixed effects serve as our measure of bank-level IT adoption. To the best of our knowledge, this is the first paper to use this type of data to study financial firms.

To understand the channels through which high IT adopters succeeded in containing the surge in NPLs during the crisis, we analyze the performance of mortgages originated before 2007 and sold to Freddie Mac, one of the two large government-sponsored enterprises (GSEs). We find that mortgages sold by high-IT adoption banks were significantly less likely to be delinquent during the GFC than the ones sold by other banks. Therefore, the better performance of high IT adopters during the crisis is driven—at least in part—by the screening of borrowers at origination.

This result has important implications for financial stability. If high IT adopters were only better in offloading their bad loans to GSEs, such as Freddie Mac and Fannie Mae, then IT intensity would not enhance financial stability but instead lead to risk-shifting and exacerbate moral hazard. 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

²We use the word “branch” as a general term for any bank establishment, including national or local headquarters and other offices.

³Later 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 this other measure of IT-adoption. For example, the correlation between the per capita share of PCs and the IT budget is 65% on the branch level. Unfortunately, these alternative information is not present in the pre-2007 survey waves.

is that 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 and was not associated with a transfer of risk across parties.

The Freddie Mac data allows us to use granular loan-level characteristics in our analysis. The results are robust to the inclusion of postal code and origination-year fixed effects, mitigating the concern that the baseline results are driven by differences in the location of high and low IT adopters. Furthermore, the loan-level characteristics help us understand what type of information management drives the results. We control for the credit-score, the debt-to-income ratio, and the loan-to-value ratio of the borrower. These information are strong predictors of default and the most important “hard” information. If banks that adopted more IT had just better access to these data, the effect of IT adoption on delinquency would vanish. Our results are, instead, unchanged when we control for these characteristics in a linear regression or probit model. These results indicate that IT-adopters had either additional information available or they used these variables in a more sophisticated and effective manner.

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 banks’ top executives (Chief Executive Officers, Chief Operational Officers, Chief Financial Officers, and Presidents) hired before 2007. Since our analysis shows that branch-level IT-adoption is mainly driven by parent bank characteristics and not by the region where the branch is based, we focus on the leaders of the parent banks. 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 also experienced lower NPLs during the crisis. 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.

The demand for IT equipment and its productivity have been associated with firms’ organizational forms, managerial quality, and human capital (Bresnahan et al., 2002; Bloom et al., 2012; McElheran and Forman, 2019). More tech-savvy banks might also have adopted superior managerial practices or hired more educated employees. Therefore, a potential concern is that the better performance during the crisis was caused by these complementary inputs rather than IT itself. We do not have data on banks’ managerial practices or employees’ education and thus we cannot completely rule out this alternative explanation. However, we can proxy for workers’ human capital with their wages (Becker, 2009) and show that (a) IT-adoption is uncorrelated with the average pre-crisis wage and the baseline results are unchanged if we include this variable as a control (b) the impact of managers’ “tech-orientation” on NPLs and IT adoption is completely unchanged if we augment the specifications with managers’ compensation or the variable

share of their compensation (the latter can be thought as a measure of risk-taking incentives [Meiselman et al. \(2018\)](#)). These empirical exercises mitigate the concerns that our results are driven by unobserved banks' organizational or managerial quality and that our measure of executives' "tech-orientation" is capturing only their overall human capital. A residual concern is that more "tech-savvy" people are simply better at creating or sustaining lending practices for some unknown reason. Under this scenario, our results would still be relevant insofar as new players, such as FinTech (or the financial arms of "BigTech" firms), or more IT-oriented banks hire larger shares of employees with an IT background relative to more traditional lenders.

Our results suggest that technology adoption in lending can enhance financial stability through better monitoring and screening. The strong increase in NPLs during the GFC impaired the functioning of the financial system ([Berti et al., 2017](#); [BIS, 2017](#)). While the increase in NPLs may not be sufficient for a full assessment of financial stability, it has been widely considered to be an important indicator for banking sector distress ([Demirgüç-Kunt and Detragiache, 2002](#)) and has been shown to have severe adverse macroeconomic consequences ([Peek and Rosengren, 2000](#); [Caballero et al., 2008](#)). To investigate whether IT adoption indeed has an impact on the functioning of the financial system, we finally investigate the lending dynamics of the banks in our sample. We find that banks that adopted less IT before the crisis and banks which had higher NPLs in the crisis had significantly weaker loan growth in the crisis.

An obvious limitation of our approach is that the type of technologies employed by commercial banks in the early 2000s might be different than today's use of machine learning and big data. On the other hand, we can examine a period of severe and systemic turmoil while the growing FinTech literature cannot. Another strength of our approach is that it is likely to be more representative since our sample covers the vast majority of lending in the pre-crisis period, while FinTech is still a small fraction of credit markets.⁴ Because of these important trade-offs the results presented in this paper should be seen as a relevant complement, rather than a substitute, to this literature.

The rest of the paper is structured as follows. In [section 2](#) we present a brief review of the relevant literature; in [section 3](#) we describe the several databases used; in [section 4](#) we present the main results on IT adoption and NPLs; in [section 5](#) we present additional results on mortgages performance, banks' top executives, and credit growth; in [section 6](#) we conclude and discuss the relevance of our results for the ongoing policy debate.

⁴ [Claessens et al. \(2018\)](#) use data from the Cambridge Centre for Alternative Finance and estimate FinTech credit to be 4% of the overall US market.

2 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. Because of its dynamism and breadth of scope, this literature is difficult to summarize and a surely non-exhaustive list includes [Jagtiani and Lemieux \(2017\)](#); [Hughes et al. \(2019\)](#); [Fuster et al. \(2018, 2019\)](#); [Berg et al. \(2019b\)](#); [Di Maggio and Yao \(2018\)](#); [Buchak et al. \(2018\)](#); [Basten and Ongena \(2019\)](#); [Bartlett et al. \(2018\)](#); [Philippon \(2019\)](#); [Hau et al. \(2018, 2019\)](#); [Stulz \(2019\)](#); [Carlin et al. \(2019\)](#); [D’Acunto et al. \(2019\)](#); [Rossi \(2018\)](#); [Navaretti et al. \(2018\)](#). While most of these papers view FinTech as a positive development,⁵ the FinTech era has not yet exposed to an adverse shock yet and therefore it is difficult to understand its impact on financial stability. We contribute by evaluating the impact of IT-adoption in lending on financial stability and by studying both “normal times” and a severe systemic shock. Moreover, the data used in several papers of this literature are obtained from a single firm, e.g. [Berg et al. \(2019b\)](#), raising questions on the external validity of the results for financial stability. In contrast, our bank sample covers the vast majority of bank loans in the US.

A large literature has studied the demand for IT across different non-financial firms or geographical units and its effect on real outcomes, such as productivity and local wages. For instance, see [Akerman et al. \(2015\)](#); [Autor et al. \(2003\)](#); [Brynjolfsson and Hitt \(2003\)](#); [Bloom et al. \(2012\)](#); [Beaudry et al. \(2010\)](#); [Bresnahan et al. \(2002\)](#); [Bloom and Pierrri \(2018\)](#); [Forman et al. \(2012\)](#); [McElheran and Forman \(2019\)](#); [Bessen and Righi \(2019\)](#). We contribute by using similar data and methodologies to study financial firms and financial stability.

Closer to us, in this respect, are a few papers that analyze certain features of IT adoption in banking before the GFC. [Beccalli \(2007\)](#) show that there are small productivity improvements from using IT in normal times. [Berger \(2003\)](#) argues that technology in banking led to improvements in cost and lending capacities. More recently, [Koetter and Noth \(2013\)](#) use IT data from Germany to re-estimate bank productivity with IT expenditure and they show that productivity is upward biased if IT expenditure is ignored. Compared to these papers we contribute by focusing on the effect of IT adoption across banks on their performance when a system-wide shock hits. Moreover, our paper provides a potential explanation for the “profitability paradox” ([Beccalli, 2007](#)): banks are heavy adopters of IT despite the small or negligible observed profitability gains in normal times because it may increase their resilience to large shocks.

This paper is also related to the recent literature studying the increasing use of data in financial mar-

⁵For instance, [Berg et al. \(2019b\)](#) show that default prediction can be improved using borrowers’ digital footprint, [Bartlett et al. \(2018\)](#) find that algorithmic lending reduces racial disparities, [Jagtiani and Lemieux \(2017\)](#) show that Lending Club provides credit especially to areas that lose bank branches and in highly concentrated banking markets, and [Carlin et al. \(2019\)](#) argue that the introduction of a mobile application for a financial aggregation platform improves borrowers’ decision-making and lead them to take less high-interest unsecured debt and pay lower bank fees.

kets (Bai et al., 2016; Farboodi et al., 2018). Our work differs because we focus on bank lending rather than asset pricing and trading.

We contribute to the literature on information in lending as advances in IT change 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). In the loan-level analysis we find that the impact of IT-adoption on loans' performance is robust to the inclusion of the most important predictors of default at origination in a linear regression or probit model. This indicates that either the high-IT lenders used additional information in the application decisions or they had a more sophisticated and effective way to use these data. While it would be interesting to distinguish between these two hypotheses, they have similar implications for financial stability.

New financial innovation can create moral hazard issues (Rajan, 2006). For instance, Keys et al. (2010, 2012, 2009) show that securitization led to lax screening. We show that banks with more IT adoption did not offload low-quality loans to GSEs, mitigating the concern that IT adoption also had a destabilizing impact through securitization. In contrast, we show that IT adoption has a first-order beneficial effect on financial stability.

We contribute to the literature that focuses on the determinants of loan-performance in the crisis by highlighting the importance of lenders' technology. Besides, we find that larger banks and banks with more loans and wholesale funding had more NPLs in the crisis. Also, banks with more geographical exposure to the house price shock had more NPL than other banks. As in Mian and Sufi (2009) and Mian and Sufi (2011), we find that borrowers with lower credit scores and higher debt-to-income or loan-to-value ratios have higher probabilities of becoming delinquent.

We finally contribute to the literature highlighting the importance of top executives for firms' outcomes (Benmelech and Frydman, 2015; Bennedsen et al., 2006; Bertrand and Schoar, 2003). We document that the "tech-orientation" of the top executives of certain banks was an important factor in promoting IT adoption, which led to fewer NPLs during the GFC.

3 Data and Measurement

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.⁶

⁶See [here](#) for more details.

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). Our main dependent variable is the amount of NPLs scaled by total assets. 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 4](#).⁷ [Figure A1](#) 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 after winsorization. Cross sectional averages and standard deviations of the main variables are provided in [Table 2](#). We winsorize all bank-level ratio at top 2.5 percent before taking averages, but results are robust to different treatment of outliers.

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 standalone establishment, 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 both as a share of employees is very strong for later years, e.g. 65% in 2016. The R-squared of a cross-sectional regression of PCs per Employee on the per capital IT budget is 44%. 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.

We focus only on establishments in the banking sector (based on SIC2 classification) and drop sav-

⁷We 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 5.3](#). 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.

ings 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. We map 90% of the assets from the bank-level dataset to the IT data.

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 years 1999, 2003, 2004, and 2006:

$$PCs/Emp_{i,t} = \widehat{IT}_b + \theta_{type} + \theta_c + \theta_t + \gamma \cdot Emp + \epsilon_{i,t} \quad (1)$$

where $PCs/Emp_{i,t}$ is the ratio of computers per employee in branch i survey wave t (capped at top 1%), \widehat{IT}_b is a bank fixed effect, θ_{type} is a establishment-type (HQ, standalone, branch) fixed effects, 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 variation is explained by the bank fixed effect 60%. The year fixed effect explains 11%. The location of the establishment only explains 27% of the variation and the number of employees' and the bank types variables explanatory power is close to zero.

Our measure of IT adoption, IT_b hereafter, is a standardized version of the bank fixed effect. It is obtained by dividing \widehat{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 A1](#) plots the cross-sectional distribution of IT_b . We also check that our results are robust to an aggressive winsorization (5 % on both sides) of this variable.

We also compute a bank-level measure of the IT adoption of local competitors. For each bank, we first take the average IT_b of other banks in each county. Then we average for each bank the IT adoption of other banks across counties.

House Price Data

As an additional control, we compute a variable that is capturing the exposure to the downturn in house prices, *HP Exposure*. We obtain county-level home value index from Zillow.⁸ For each county we con-

⁸See [here](#) for more details.

struct the percentage change in the annual average house price decrease between peak (2012 Q3) and trough (2007 Q4). We merge the county level decrease in the house price to the IT establishment data by county. We construct the exposure to the house price decrease by taking the median decrease in the house price index across establishment for each bank.

Freddie Mac Data

We use the Single Family Loan-Level Dataset from Freddie Mac.⁹ The loan-level dataset covers the performance on mortgages that Freddie Mac bought starting in 1999. The data includes higher-quality loans which had to conform to agency guidelines (Adelino et al., 2016). We use the provided information on the postal code, credit score *FICO*, loan-to-value *LTV* and debt-to-income *DTI* ratio of the borrower as well as the origination year, the seller and the delinquency status of the loan. We define a loan as delinquent past due more than 90 days. The seller of the loan is only disclosed for sellers which have at least 1% of the total original mortgage balance of all loans in a quarter. We merge the seller of the loan with the IT dataset but due to the limited number of sellers reported we only have 22 banks with information on technology adoption.

Data on 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, 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 and the non-base share of the compensation, e.g. bonuses. This is in spirit of Meiselman et al. (2018) who construct a comprehensive dataset of CEO compensation complementing the Standard & Poor's Executive Compensation database. They show that higher payouts to CEOs are associated with significantly higher tail risk exposure.

⁹See [here](#) and [Goodman and Zhu \(2015\)](#) for a detailed description and summary statistics. The dataset is also used by [Adelino et al. \(2016\)](#) and [Bartlett et al. \(2018\)](#).

4 IT adoption and NPLs

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 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 2011.¹⁰

4.1 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 level of IT adoption experienced different levels of NPLs during this period, we rely on the following panel equation:

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

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 3](#), 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 that may be associated with NPLs during the crisis. The vector contains several pre-crisis bank characteristics: the ratio of loans to assets, the size as measured by the log of total assets, the share of capital over assets, the share of wholesale funding over assets, ROA, and the log of average wages.¹¹ We also include two controls capturing the geographic distribution of banks' branches. The first one measures the exposure to the house price drop, while the second one constructs the IT adoption of other banks operating in the same location. 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. Since we include bank fixed effects, the variables IT_b and X_b appear only interacted with the crisis period dummy.

[Table 1](#) presents the results from estimating different version 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

¹⁰The dynamics of NPLs for bank with intermediate adoption lies between the low- and high- adopters in most years, see [Figure A2](#). 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 A3](#), finding a very similar pattern.

¹¹We take the simple averages between 2001 and 2006 to measure pre-crisis levels; however, results are unchanged if we use a different pre-GFC window, such as 2004-2006.

the above equation. Column (1) shows the results of [Table 1](#) without the inclusion of bank fixed and year fixed effects and without controls. The base effect of technology adoption on non-performing loans is negative but 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 times 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 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)-(12) successively introduce additional controls to the baseline specification with only bank and year fixed effects. We start by controlling for the share of loans relative to assets in the pre-crisis period as a control. Banks that had more loans as a share of assets had a stronger increase in NPLs, as expected. Next, we introduce the exposure to the drop in house prices. We compute this exposure by weighting the drop in county-level house prices by the number of branches a bank has in this county. Banks that had more branches in counties in which house price dropped more suffered a stronger increase in NPLs. In column (7), we include the size of the bank interacted with the crisis dummy as an additional control. Consistent with [Sullivan and Vickery \(2013\)](#) larger banks had a stronger increase in NPLs in the crisis than smaller banks. The pre-crisis capital position, the pre-crisis wholesale funding and the return on asset ratio, as well as the average wage of the banks' employees did not have a significant impact on NPLs in the crisis.

Lastly, we add the IT of local competitors as an additional control variable. This variable can 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. Column (12) 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 banks, where their local competitors did not adopt IT intensively. This evidence suggests that IT adoption does not have negative spillover effects to local competitors.

In [Table A1](#) we conduct several robustness test of [Equation 2](#). Column (1) repeats the baseline. Column (2) uses another measure of IT adoption. Instead of using the bank fixed effects from [Equation 1](#), we take the average share of PCs per employee across branches for each bank. While the disadvantage of the approach is that we do not control for branch-specific characteristics that drive the share of PCs per employee of the branch, the results still hold with this simpler measure. In column (3) and column (4) we provide robustness with a stronger winsorization of the IT adoption measure and NPLs, respectively, to reassure our results are not driven by outliers. In column (5) and (7) we use a different denominator for our dependent variable. In column (5) we divide by the overall loans of the bank while in column (7) we divide by the pre-crisis assets to ensure the denominator is not driving our results. Column (6) uses a different definition of NPLs. In the baseline, we classify loans to be non-performing if the loan is past due 90 days or more. In column (6) we use a broader classification by including loans if the loan is past due 60 days or more. Finally, column (8) shows results when the standard errors are clustered at the bank-level instead of double clustered at the bank and year level.

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:

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

The coefficient of 2006 is normalized to zero. Results are illustrated in [Figure 2](#). The red dot shows the point estimates of the interaction between the IT adoption and the year dummies, β_τ , with the black bars reflecting the 95%, and the grey shaded area the 99% confidence interval, according to standard errors double clustered at the bank and year level. 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 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.

4.2 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:

$$Y_b = \alpha + \beta \cdot IT_b + \epsilon_b \quad (4)$$

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.

Table 2 present the relative 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 very 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 that could be important in driving NPLs in the post-crisis period. We include several pre-crisis variables to capture banks' business model, profitability, and capital structure: ratio of loans, wholesale funding, and capital to assets, and ROA. We compute banks' exposure to the house price shock using the drop in house price for each county (peak to trough) and the pre-crisis geographical distribution of branches. We also use the log of pre-crisis assets to measure bank size, and the log of average wage as a proxy for employees' human capital. We find that IT adoption is not significantly related to any of these characteristics.¹² Moreover, the R-squared of column (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 "falsification" 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.

We measure the IT adoption of banks' competitors by relying on the pre-crisis geographical distribution of branches. We find a positive correlation between the banks' own IT adoption and its competitors'.

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 ten-fold increase in R-square. This suggests that the equation of column (1) does not suffer from an omitted variable bias and pointing towards a causal relationship between IT adoption and NPLs (Altonji et al., 2005; Oster, 2019). Oster (2019) provides formal statistical procedures to assess the stability of OLS coefficients

¹²We compute additional variables, such as the share of residential or personal loans over the total amount of loans, and find no correlation of these variables with IT adoption either. Additionally, in subsection 5.1 we present direct evidence that the impact of IT on NPLs is not driven by location of lending activities.

to the inclusion of relevant control and test for the potential bias arising from the presence of other unobservable variables. We apply these procedures and find that the coefficient on IT adoption compatible with the inclusion of all unobservable variables is minus 14 basis points, which is similar to baseline and well below zero.¹³ Therefore, our results seem to be robust to the presence of unobservable variables.

Some of the bank characteristics are important for the share of NPLs in the crisis period. Similarly to Table 1, banks with more loans and stronger geographic exposure to the house price shock suffer higher levels of NPLs. Besides, we find that banks that had more wholesale funding had larger increases in NPLs. Importantly, as in Table 1 the IT adoption of local competitors in the pre-crisis period did not have a significant impact on the increase in NPLs in the crisis period, suggesting that there are no negative spillover effects of IT adoption.

5 Additional Results

In this section, we rely on multiple data sources to study the mechanisms behind the effect of IT adoption on NPLs, the sources of heterogeneity in IT intensity, and the impact of IT and NPLs on credit dynamics.

5.1 Loan-Level

We use the Single Family Loan-Level Dataset to study the performance and characteristics of mortgages originated by banks with heterogeneous degrees of IT adoption and sold to Freddie Mac. This analysis is useful to investigate the channels through which high IT adoption banks were able to limit the surge in NPLs. We estimate the following loan-level equation:

$$Delinquent_l = \alpha_{z(l)} + \delta_{o(l)} + \beta \cdot IT_{b(l)} + X_l' \gamma + \eta_l \quad (5)$$

where l is a mortgage held by Freddie Mac and originated before 2007 by a commercial bank in our IT sample; $Delinquent_l$ is either the fraction of months, within the crisis period, during which the loan is delinquent or a dummy variable indicating whether the loan has ever been delinquent during the same period. For consistency with the bank-level regressions, we flag a loan as delinquent if it has a past due 90 days or above and we define the crisis period as the years between 2007 and 2010.¹⁴ $\delta_{o(l)}$ are fixed effects for the year of origination and $\alpha_{z(l)}$ are fixed effects for the 3-digit postal code of the underlying property. While the origination-year fixed effects capture for example business cycle dynamics, the postal code

¹³This test has been used in other empirical studies in finance and economics, such as Mian and Sufi (2014). Following Oster (2019) jargon, we set the “hypothetical R-square” to 1, which is the most conservative choice. We find a treatment effect of -.14 and a relative degree of selection above 1. These results are valid under the assumption of “proportional selection of observables and unobservables” that is discussed in Altonji et al. (2005), Oster (2019), and Finkelstein et al. (2019).

¹⁴The results are robust to flagging loans to be delinquent if they have been past due for different periods.

fixed effects control for local heterogeneity that can arise, for instance, from the severity of the Great Recession and or from different house market dynamics. IT_b is bank-level technology adoption. Freddie Mac data does not report the name of all mortgage sellers, so we can only match 22 commercial banks. X_i is a vector of mortgage characteristics at origination: borrower's FICO score, Loan-to-Value (LTV) ratio, and Debt serving-to-Income (DTI) ratio.

Table 3 reports estimates of different versions of subsection 5.1, together with standard error clustered at the seller level. The equation is estimated with OLS except that for the last column where we rely on a probit model. Dependent variables are multiplied by 100 (except for the last column) while independent variables are normalized to have mean zero and unitary standard deviation so that coefficients are easily comparable. Column (1) shows without any controls that loans sold by technology adopters were delinquent fewer months in the crisis than other loans. Columns (2) and (3) include year-of-origination and location fixed effects and column (4) add the vector of mortgage characteristics at origination. All specifications illustrate that mortgage sold by banks with higher IT adoption spent a significantly smaller fraction of time in a delinquent status during the crisis. A loan that has been originated by a bank with a one standard deviation higher IT adoption has been delinquent 32 basis points fewer share of the time, i.e. around 10% less than the average loan.

The magnitude of this relationship is not trivial compared to loan-level characteristics that have been shown to be important predictors of default: a one standard deviation higher IT adoption has the same predicted effect on delinquency that a third of a standard deviation lower LTV ratio, half of a standard deviation of lower DTI, or 13% of a standard deviation higher FICO score. In column (5) 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 (6) and (7) we show that the results are qualitatively the same if we use a Linear Probability Model or a Probit Model to estimate the impact of IT adoption and mortgage characteristics on the probability that a mortgage has ever been delinquent during the crisis period.

The loan-level analysis serves multiple purposes. It allows us to dig deeper into the mechanisms behind the relationships between IT adoption and NPLs. It shows that at least part of the effect we document in subsection 4.1 is due to the origination of more resilient loans before the crisis rather than other channels, such as a better ability to manage or dismiss NPLs. For instance, if the effect of IT on delinquencies for loans which are still on banks' balance sheets would solely come from banks better ability to collect mortgage payments, we would not expect the same effect for off-loaded mortgages.

It also 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 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 not enhance financial stability.

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 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. Hence, the IT adoption of banks seems to give banks an informational advantage regarding the mortgage and not only about the location of the borrower or the business cycle.

We can also control for a few of the most important characteristics that predict mortgage performance at origination: the borrower FICO score, the LTV, and the DTI ratios. We find that the impact of IT on delinquency does not disappear if we control for these characteristics in a linear fashion. This implies that either high-IT adopters had additional information available that affected their lending decisions or had more sophisticated ways to use these variables when deciding whether and how much to lend to a borrower.¹⁵ It would be interesting to understand whether superior IT adoption allowed some banks to store, disseminate, and use additional information, perhaps “hardening” some otherwise “soft” information, or to employ more effective prediction systems (or both). However, distinguish between these hypotheses is not of first order importance for the financial stability focus of this paper.

In unreported results we find that IT adoption is uncorrelated with the default predictors mentioned above. This suggests that the high-IT adopters did not just choose to focus on a safer segment of the market before the crisis but actively selected better borrowers. Moreover, the availability of the FICO score allows us to investigate which types of mortgages were most affected by IT availability. We find that the delinquency rate is affected by IT adoption only for mortgage issued to borrowers with credit scores below the sample median.

The loan-level analysis has also some drawbacks. We can only match 22 banks with the dataset on IT adoption, limiting the statistical power of our analyses and our ability to further investigate the differences in lending practices between high- and low-IT adopters. Moreover, the loans in this dataset differ in some characteristics, such as the average credit score, compared to the portfolio of loans which were kept on the balance sheet of banks (Keys et al., 2010).

5.2 Executives' Background

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

¹⁵For example, more IT might have allowed these banks to sustain more reliable internal rating systems. We refer to Berg (2015) and Berg et al. (2019a) for a description of internal rating systems.

Economists have documented huge—and interrelated—dispersion in firm- and plant-level productivity (Syverson, 2011), management practices (Bloom et al., 2019), and IT adoption (see references in section 2). While a complete understanding of this dispersion is far from being accomplished, a robust literature has highlighted several relevant factors. In particular, it has been shown that frictions of different natures, such as lack of proper information (see Section VI.A in Bloom et al. (2013)), incentives (Atkin et al., 2017), or financial constraints (Duval et al., 2019; Manaresi and Pierri, 2019), have a prominent role in preventing or slowing down the adoption of superior practices and technologies.

A related strand of literature documents the importance of characteristics and background of executives for firm outcomes and performance (Benmelech and Frydman, 2015; Bennedsen et al., 2006; Bertrand and Schoar, 2003). Therefore, we conjecture that top executives that have a more tech-prone background and orientation may be important to overcome these frictions and promote a higher degree of IT adoption in the banks they lead.

The focus on bank’s top executives is also grounded in the descriptive patterns documented in section 3: the explained variation in technology adoption at the branch-level is driven by bank characteristics (60%) relative to geographic characteristics (27%).

To capture the tech-orientation of the top executives (CEOs, CFOs, COOs, and Presidents) hired before 2007, independently of whether they are still active, we search for tech-related keywords in their biographies, as described in section 3. We compute an overall score for each bank regarding the “tech-intensity” of their executives. We can then match regulatory data, IT adoption, and executive biographies data for 249 banks. We estimate the following cross-sectional regression model:

$$Y_b = \alpha + \beta \cdot ExecIT_b + \epsilon_b \tag{6}$$

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 pre-crisis IT adoption or the level of NPLs over assets during the crisis period. Both independent variables are standardized to have mean zero and variance one.

Results are presented in Table 4. Column (1) repeats the baseline specification on this sub-sample of banks, finding similar results than in Table 2 (although slightly smaller and noisier). Column (2) shows that banks led by more tech-oriented executives experienced lower NPLs during the crisis. Column (3), instead, shows that executives’ background is a significant predictor of bank’s IT adoption. Columns (2) and (3) are consistent with our hypothesis that tech-prone executives were instrumental in leading banks to adopt IT more intensively and experience the related benefits afterward. The lower statistical significance of the coefficient in column (3) vs (2) may be due to differences in data sources: the left-hand side variable of column (2) is measured from regulatory data rather than a survey, and therefore it is likely to contain less measurement error.

Under the assumption that executives' tech-orientation affects banks only through IT adoption, we can use it as an instrument for the main specification of column (1). Below we provide some additional evidence supporting the validity of such an instrument. However, the regression of executive tech-orientation on IT adoption delivers a low R-square and an F-stat of 4. Therefore, while we argue that this instrument would be consistent, the IV estimates are likely to suffer from a sizeable finite-sample bias due to the "weak instrument" problem. We nonetheless report these estimates in column (4). The estimated coefficient of IT adoption is negative and statistically different from zero. However, it is of an order of magnitude larger than OLS, possibly because of poor small-sample properties.

A potential concern with the results of [Table 4](#) is that the tech-orientation of executive may be capturing in general higher human capital of these executives. If tech-prone executives are just better managers, then the impact on NPLs may be due to better management practices unrelated to IT itself. We therefore re-estimate [Equation 6](#) including the (log of the) pre-crisis compensation of the executives as a control. Results, reported in [Table 5](#), are absolutely unaffected by the inclusion of such a control. Moreover, compensation itself does not have explanatory power either for NPLs during the crisis nor for IT adoption before the crisis. Insofar as compensation can be used as a proxy for human capital ([Becker, 2009](#)), these results show that is specifically tech-orientation, and not general quality or skills, that matters for our variables of interests. Furthermore, the results are unaffected to the inclusion of the non-base share of total compensation, that can shape risk-taking incentives ([Meiselman et al., 2018](#)), as reported in [Table A2](#).

A further concern is that the list of words used to measure tech-orientation of executives from their biographies is somehow ad-hoc. We, therefore, test the robustness of our results to the choice of words. For each word, we compute an additional tech-orientation measure based on all the remaining words. We then re-estimate the cross-sectional regressions with each of the different tech-orientation measures. We plot the estimated coefficients in [Figure A4](#), where panels top to bottom refer to the columns (2) to (4) in [Table 4](#). We find that all our results are robust to the use of exclusion of any word in the list, as (a) the coefficients are all clustered around the estimates of [Table 4](#) (flagged by a dashed lined) and fairly close (b) all have the same sign (negative in top and bottom panels and positive for the mid panel).

The results presented in this section are informative about the roots of the dispersion in IT adoption. Moreover, they are a strong support for the causal interpretation of the relationship between IT and NPLs. In fact, they point towards IT as the cause of the lower NPLs during the crisis, rather than other unobservable characteristics, such as the quality of management practices.

5.3 Bank Lending

High levels of NPLs weigh on banks' profitability and can, therefore, 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 3 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 the lack of pre-crisis correlation between lending intensity and IT documented in Table 2. 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 from 2012 but the difference is still present in 2014. These patterns suggest that heterogeneity in IT adoption, perhaps through the impact on NPLs documented in section 4, has a role in explaining banks' different lending dynamics during and after the crisis.

In this section, we formally test whether banks with fewer NPLs during the crisis and with higher IT adoption were lending more during the crisis. We follow Peek and Rosengren (2000) in defining lending as the change in loans over total assets and, as in the rest of the paper, we take the average across the crisis period. We estimate the following cross-sectional specification:

$$\overline{\Delta Loans}_b^{GFC} = \alpha + \beta \cdot X_b + \epsilon_b \quad (7)$$

where X_b either the share of NPLs in the crisis period or the pre-crisis IT adoption. Results are presented in Table 6 and each regression is estimated with and without the set of controls discussed in subsection 4.2.

Similarly to Peek and Rosengren (2000), we find that a 100 basis points higher NPLs to assets ratio is associated with about 100 basis lower average loan growth. We also show a significant impact of IT adoption on lending: one standard deviation increase in IT adoption is associated with a 33 basis points higher loan growth during the crisis, which is about 20% of its mean.

These results show that IT adoption helped banks providing credit during (and after) the GFC. It is difficult to know whether IT adoption had an impact only because it mitigated the surge in delinquency rates (subsection 5.1) and NPLs (section 4) or it also improved banks' ability to function during the shock and expand afterward in other ways. In either case, our results indicate that IT intensity improved financial stability during the GFC.

6 Conclusion

As the financial industry becomes more and more reliant on Information Technology, as exemplified by the surge of FinTech players, it is extremely policy-relevant to understand the consequences for financial stability of a more intense use of IT 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 relative to other banks and provided more credit to the economy during the crisis. High- and low-IT-adopters were not differentially exposed to the GFC in terms of pre-crisis geographical footprint and business model. Moreover, loans originated by high-IT banks experienced lower delinquency rates during the crisis even when they were securitized and sold to Freddie Mac. Therefore, our results indicate that IT-adoption helped banks to select better borrowers and produce more resilient loans. We finally show that the roots of this heterogeneity seem to be partially related to the “tech-orientation” of their top-executives, which we capture with a simple text-analysis algorithm.

The evidence presented in this paper suggests that the “FinTech era” is likely to be beneficial to financial stability. The main caveat of our analysis is that the technologies adopted by commercial banks before the GFC might be significantly different than the ones that banks, FinTech firms, and financial arms of BigTech companies are implementing nowadays.

We offer three main considerations to support the relevance of our results despite this obvious limitation. First, our measure of IT-adoption, while based on the simple counting of computers divided by the number of employees within a branch, is still informative about technological intensity more broadly defined in very recent years. A simple regression of this measure against the overall IT-budget of an establishment in 2016 delivers an R-square of 44% and a correlation coefficient of 65%. Moreover, the adoption of frontier technologies, such as Cloud Computing, is also positively correlated with our simple measure.

Second, many of the IT-driven changes in the financial industry are so recent that they have not experienced yet—at the time of the writing— a large systemic shock testing their resilience. In addition, the share of lending provided by “FinTech” firms is still small in most countries. Therefore, it is important to collect the best possible empirical evidence from past systemic shocks to inform the current debate. Analogously, despite the ever-changing features of economies and financial systems, the lessons learned during the Great Depression were useful in shaping the policy-response to the Great Recession (Bernanke, 2015). Conversely, ignoring evidence regarding past crises because of the observed differences with the present scenario might lead to highly undesirable outcomes (Reinhart and Rogoff, 2009).

Third, if one focuses on the lending business, there are several commonalities between the IT-intensive methods used before GFC and the most recent advancements. Statistical models to predict defaults

were widely used during the decade preceding the GFC (Rajan et al., 2015). The up-to-date machine learning techniques that are used to predict borrowers' behavior are more powerful versions of the previously available statistical tools, rather than radically different systems. In fact, introductory university courses on machine learning often list linear regressions, probit, or logit models as simple examples.¹⁶ The collection and use of new data to inform application decisions, such as the digital footprint (Berg et al., 2019b), is not conceptually different than the use of credit scores. The main difference lies in the requirements—in terms of infrastructure and know-how—to acquire, store, manage, and employ these data. The decline in the cost of computing power, that allows this progress to happen, occurs at a constant rate (Moore's law).

We conclude by underlining that, since we study IT adoption of traditional banks, we are silent on many institutional features associated to FinTech, such as the connection with shadow banking and the room for regulatory arbitrage (Buchak et al., 2018). These features may be relevant for financial stability.

¹⁶For instance, the Linear Regression is one of the two topics covered in lecture 2 of “CS229: *Machine Learning*” at Stanford University, according to the 2019 syllabus (available at <http://cs229.stanford.edu/syllabus.html>). Weighted Least Squares and Logistic Regression are covered in lecture 3.

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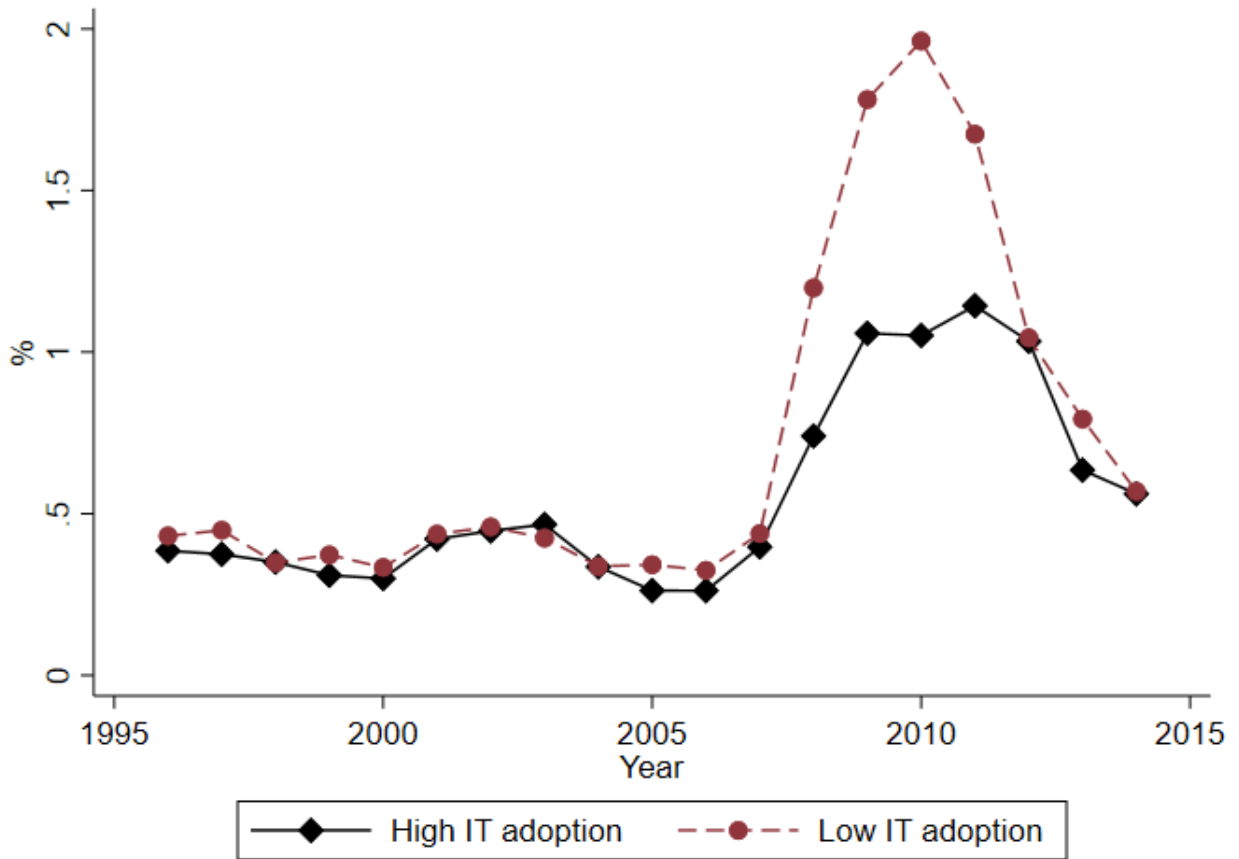
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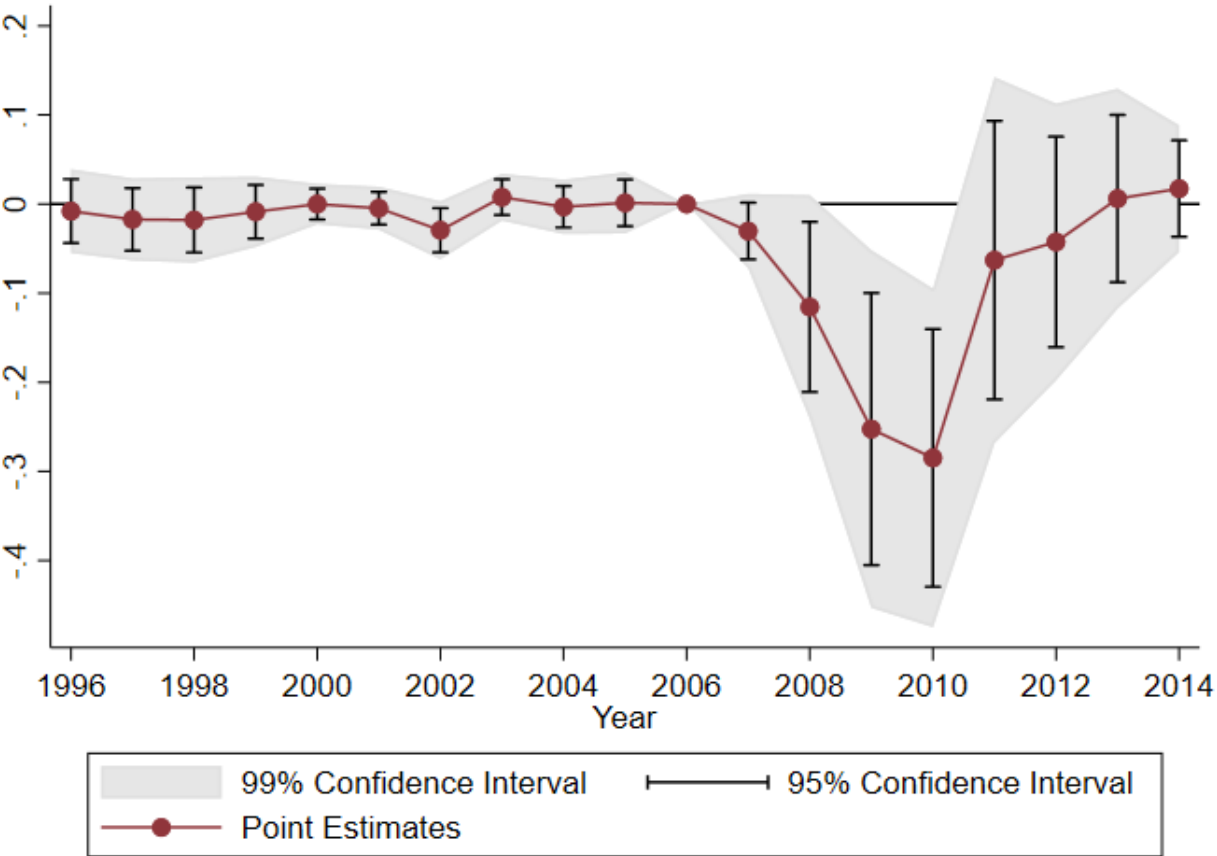
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Figure 1: NPLs over Assets by pre-GFC IT adoption



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 4.1](#) and [section 3](#) for more details.

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

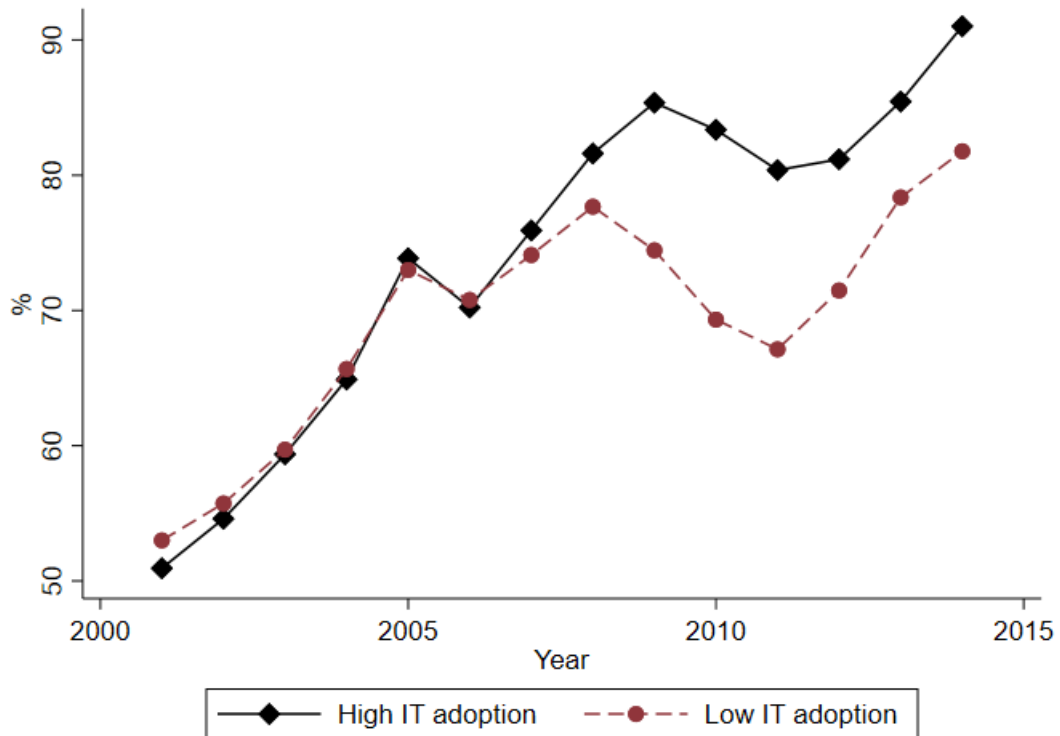


This Figure plots the coefficient and the 95% and 99% confidence intervals of β_τ from the following estimated equation:

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

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 3. 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 4.1 and section 3 for more details.

Figure 3: 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 5.3 and section 3 for more details.

Table 1: Panel Regressions

	Dependent Variable: NPLs during GFC											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
IT-adoption	-0.0230 (0.017)		-0.0280 (0.018)									
IT-adoption × crisis	-0.160** (0.063)	-0.168** (0.065)	-0.157** (0.066)	-0.170** (0.068)	-0.158** (0.063)	-0.139** (0.057)	-0.131** (0.055)	-0.131** (0.056)	-0.131** (0.056)	-0.131** (0.056)	-0.131** (0.056)	-0.143** (0.063)
Loans × crisis					0.0201*** (0.006)	0.0199*** (0.006)	0.0177*** (0.006)	0.0175*** (0.005)	0.0186*** (0.006)	0.0189*** (0.006)	0.0189*** (0.006)	0.0192*** (0.006)
HP Exposure × crisis						0.0191** (0.009)	0.0172* (0.008)	0.0172* (0.008)	0.0172* (0.008)	0.0171* (0.008)	0.0171* (0.009)	0.0174* (0.009)
Size × crisis							0.128** (0.052)	0.126** (0.050)	0.115** (0.050)	0.123** (0.055)	0.124* (0.062)	0.124* (0.062)
Capital × crisis								-0.000672 (0.005)	0.000698 (0.005)	0.000933 (0.005)	0.000805 (0.005)	0.00113 (0.005)
Wholesale × crisis									0.00831 (0.007)	0.00779 (0.007)	0.00779 (0.007)	0.00762 (0.007)
ROA × crisis										-0.0204 (0.048)	-0.0206 (0.048)	-0.0211 (0.049)
Log Wage × crisis											-0.0108 (0.125)	-0.00388 (0.124)
IT of local competitors × crisis												0.0475 (0.046)
(Within) R-squared	0.112	0.140	0.0111	0.00997	0.0363	0.0553	0.0613	0.0611	0.0621	0.0620	0.0617	0.0623
N	4608	4608	4608	4608	4608	4608	4608	4608	4608	4608	4608	4608
Bank FE	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	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 3. 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 of the observed drop in prices (peak to trough) 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. See subsection 4.1 and section 3 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

Dependent Variable:	NPLs during GFC	Loans pre-GFC	HP Exposure	Size pre-GFC	Capital pre-GFC	Wholesale pre-GFC	ROA pre-GFC	Log Wage pre-GFC	IT of local competitors	NPLs during GFC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
IT-adoption	-0.183*** (0.061)	-0.648 (0.700)	-0.896 (0.664)	-0.0931 (0.057)	-0.195 (0.420)	-0.0459 (0.372)	-0.0282 (0.049)	-0.0227 (0.018)	0.275*** (0.083)	-0.157*** (0.058)
Loans										0.0305*** (0.004)
HP Exposure										0.0242*** (0.005)
Size										0.0857 (0.077)
Capital										0.00605 (0.007)
Wholesale										0.0251*** (0.008)
ROA										-0.0452 (0.070)
Log Wage										-0.145 (0.210)
IT of local competitors										0.0773 (0.047)
R-squared	0.0262	0.00220	0.00550	0.00712	0.000427	0.0000383	0.00107	0.00414	0.0750	0.243
N	337	337	337	337	337	337	337	337	337	337
Mean	1.54	62.69	15.83	13.9	13.02	15.92	2.55	4.84	0	1.54
Std.Dev.	1.13	13.8	12.06	1.1	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 3. 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 drop in prices (peak to trough) 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 4.2 and section 3 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: Loan-Level Regressions

Dependent Variable:	Delinquency during GFC						
	Share of months with past due>90 days				Ever past due>90 days		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
IT adoption	-0.471**	-0.459**	-0.348**	-0.323**		-0.106**	-0.0377**
	(0.191)	(0.169)	(0.145)	(0.118)		(0.041)	(0.016)
FICO score				-2.578***	-1.125***	-1.042***	-0.258***
				(0.284)	(0.181)	(0.088)	(0.036)
DTI				0.565***	0.248***	0.246***	0.0994***
				(0.052)	(0.022)	(0.019)	(0.012)
LTV				1.075***	0.543***	0.541***	0.185***
				(0.129)	(0.056)	(0.058)	(0.006)
IT adoption × Low FICO					-0.198***		
					(0.064)		
IT adoption × High FICO					-0.00732		
					(0.029)		
Estimation Method	OLS	OLS	OLS	OLS	OLS	OLS	Probit
Org. Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Postal Code FE	No	No	Yes	Yes	Yes	Yes	No
N	3,451,671	3,451,671	3,451,671	3,451,671	3,451,671	3,451,671	3,451,671
Mean	3.44	3.44	3.44	3.44	3.44	1.5	.015
Std.Dev. of dept. var.	14.32	14.32	14.32	14.32	14.32	12.15	.1215

Results of estimating the following equation:

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

where l is a mortgage held by Freddie Mac and originated before 2007, $\alpha_{z(l)}$ are fixed effects for the 3-digit postal code of the underlying property, and $\delta_{o(l)}$ are fixed effects for the year of origination. $IT_{b(l)}$ is the pre-crisis IT-adoption of the bank which sold the mortgage to Freddie Mac, estimated as described in section 3 (22 banks). The dependent variable $Delinquent_l$ is either the share of months between 2007 and 2010 during which the loan was in a delinquent status (> 90 days past due) or a dummy variable indicating whether loan was ever delinquent between 2007 and 2010. Both are multiplied by 100, except than in column (7). The vector of controls X_l includes the FICO score, the debt servicing to Income (DTI), and the Loan-to-Value (LTV) ratios at origination. All independent variables are standardized to have a mean of 0 and a standard deviation of 1. Column (1) excludes all fixed effects and controls, column (2) excludes X_l and $\alpha_{z(l)}$, while column (3) excludes X_l . Column (5) interacts banks' IT adoption with a dummy variable indicating whether the borrower has a FICO score above or below the median. We also include this dummy in the regression. See subsection 5.1 and section 3 for more details. Sample size is kept constant by dropping observations with missing values for any variable. Standard errors (in parentheses) are cluster at the bank-level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: NPLs, IT adoption, and Executives’ “tech-orientation”

Dependent Variable:	NPLs during GFC (1)	NPLs during GFC (2)	IT-adoption (3)	NPLs during GFC (4)
IT-adoption	-0.138* (0.076)			-1.719* (1.044)
Executives’ “tech-orientation”		-0.155*** (0.047)	0.0900* (0.051)	
Estimation	OLS	OLS	OLS	IV
R-squared	0.0141	0.0210	0.00967	
N	249	249	249	249

Results of estimating the following equation:

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

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 1, 2, and 4), or the pre-crisis IT adoption (column 4), estimated as described in [section 3](#). The independent variable X_b is either the pre-crisis IT adoption (columns 1 and 4) or 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 5.2](#) and [section 3](#) for more details. In column (4) the IT-adoption is instrumented with executives’ “tech-orientation”. Column (3) is also the first stage of column (4). 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 5: Executives’ “tech-orientation” and Compensation

	(1)	(2)	(3)	(4)
	NPLs	NPLs	IT-adoption	IT-adoption
Executives’ “tech-orientation”	-0.173*** (0.062)	-0.168*** (0.062)	0.104* (0.057)	0.104* (0.057)
Log Compensation		-0.0375 (0.060)		-0.00208 (0.053)
R-squared	0.0226	0.0244	0.0136	0.0136
N	237	237	149	149

Results of estimating the following equation:

$$Y_b = \alpha + \beta ExecutiveIT_b + \gamma Comp_b + \epsilon_b$$

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 1 and 2) or the pre-crisis IT adoption (columns 3 and 4), estimated as described in section 3. The independent variable $ExecutiveIT_b$ 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 5.2 and section 3 for more details. The controls $Comp_b$ is the log of the average total compensation earned by top executives in 2007. $Comp_b$ is excluded in columns (1) and (3). 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 6: Lending Regressions

Dependent Variable :	Loan Growth (crisis)			
NPLs during the GFC	-0.926***	-1.030***		
	(0.159)	(0.187)		
IT-adoption			0.378**	0.331*
			(0.182)	(0.196)
R-squared	0.0127	0.0928	0.0961	0.175
N	343	336	343	336
Controls	No	Yes	No	Yes

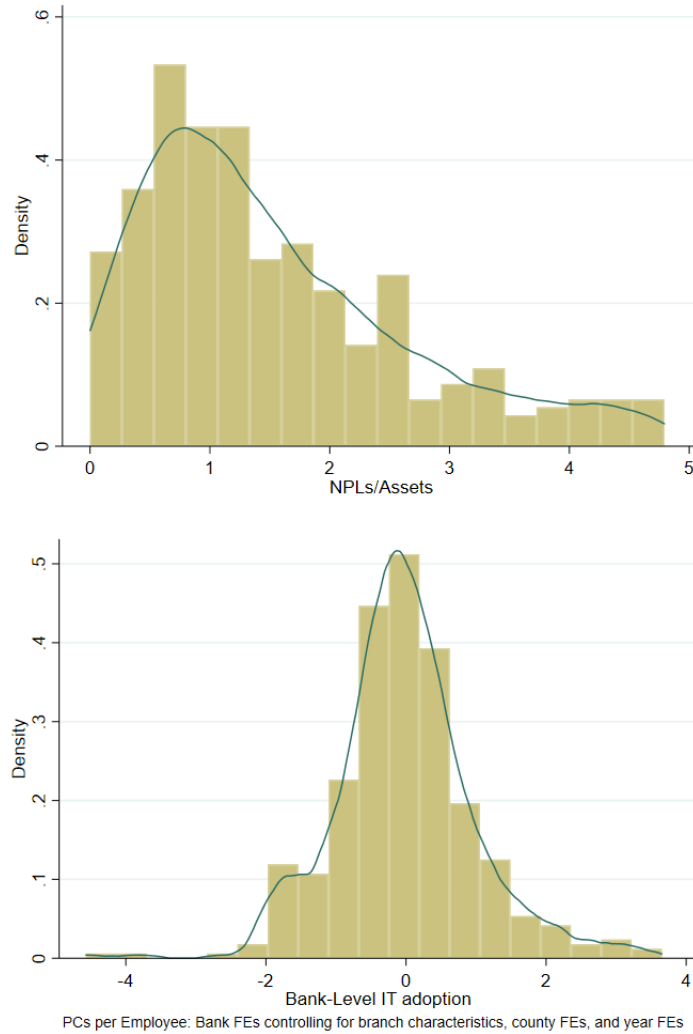
Results of estimating the following equation:

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

where b is a bank (BHC). The dependent variable $\overline{\Delta Loans}_b^{GFC}$ 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 3](#) or the share of NPLs over assets in bank b regulatory filing (averaged over 2007 to 2010). See [subsection 5.2](#) and [section 3](#) for more details. Robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

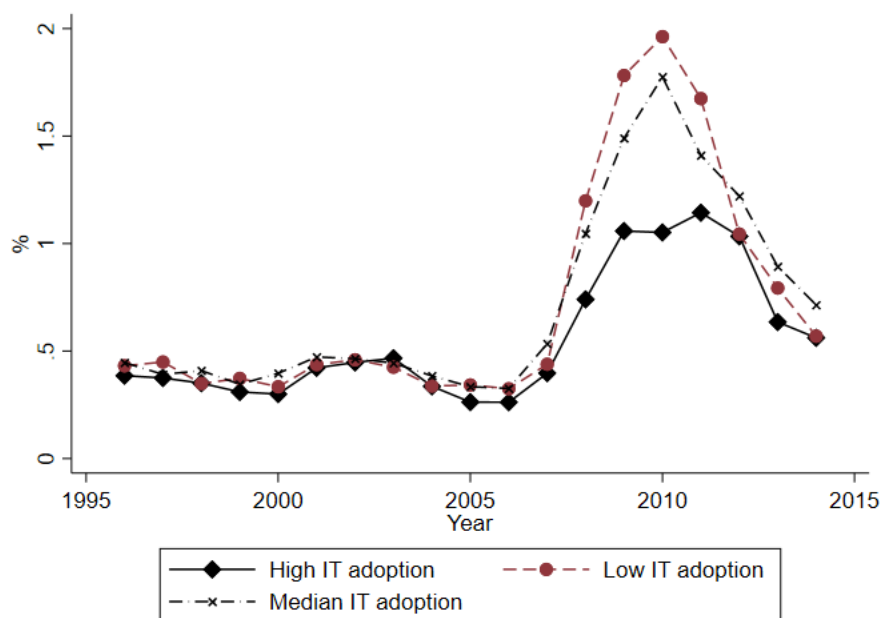
Appendix: Figures and Tables

Figure A1: Cross-sectional distribution of NPLs over Assets (crisis) and IT adoption (pre-crisis)



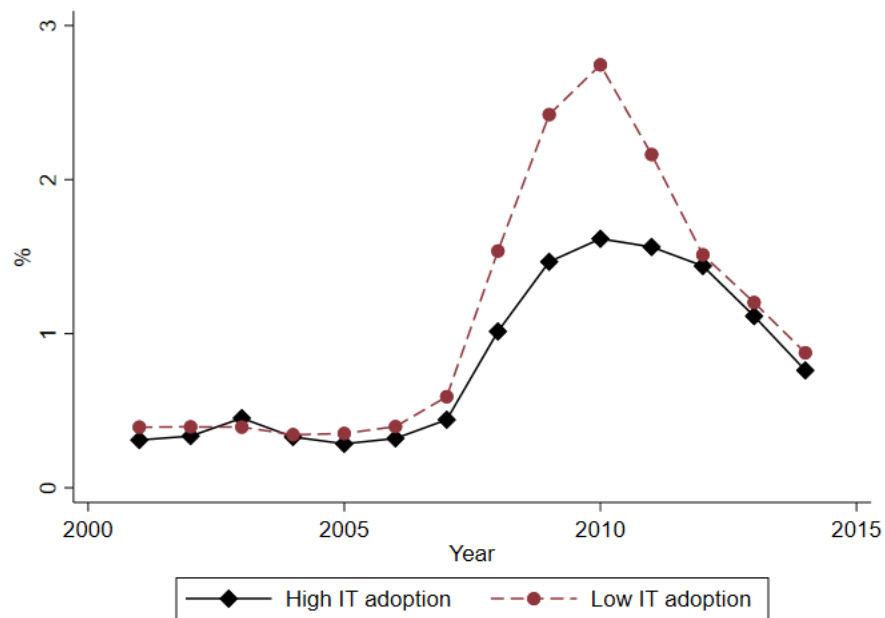
This Figure plots the cross-sectional distribution of the ratio of NPLs to assets averaged between 2007 and 2010 (top panel) and of the pre-crisis IT adoption IT_b . See section 3 for more details.

Figure A2: NPLs over Assets by pre-GFC IT-adoption



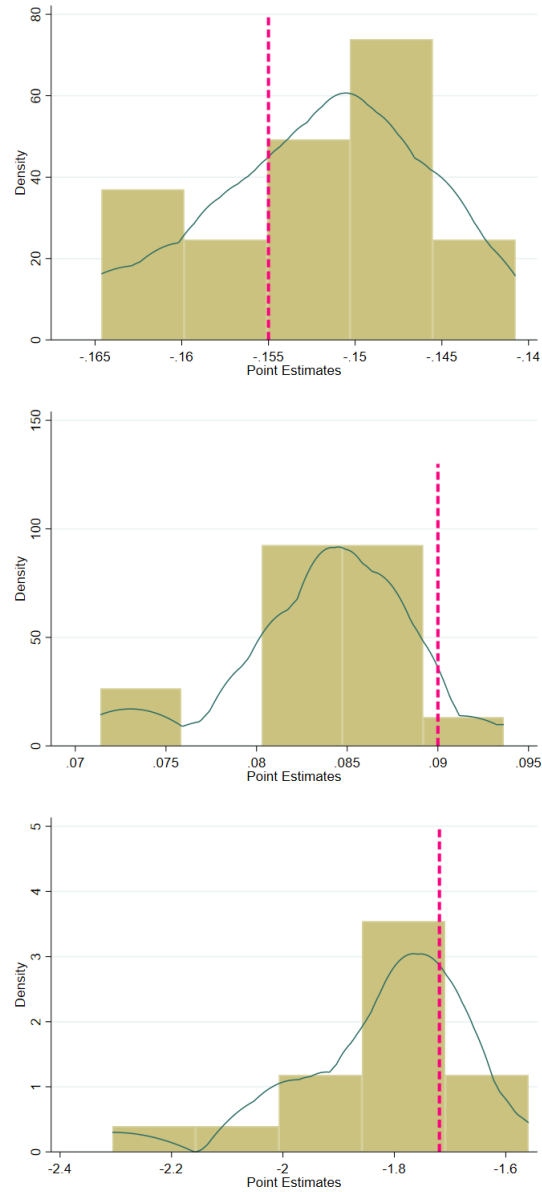
This Figure plots the median share of NPLs over assets for high, medium, and low IT adopters. “High IT adoption” is the median share of NPLs over assets for banks with IT_b above the 75th percentile. “Low IT adoption” is the median share of NPLs over assets for banks with IT_b below the 25th percentile. “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 4.1 and section 3 for more details.

Figure A3: 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 4.1](#) and [section 3](#) for more details.

Figure A4: Robustness of the Executives' results to changes in the keywords list



This Figure plots the coefficient of columns (2)-(4) 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) to (4) of Table 4. See section 5 and section 3 for more details.

Table A1: Robustness of Main Panel Regression

		Dependent Variable: NPLs							
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IT-adoption × crisis		-0.165** (0.068)	-0.243* (0.120)	-0.158** (0.069)	-0.161** (0.063)	-0.242** (0.095)	-0.214** (0.080)	-0.380* (0.183)	-0.165*** (0.051)
Exercise	Baseline	PCs per Emp	HW IT	HW NPLs	Loans	Broad def.	As of 2006	Bank Clustering	
R-squared	0.00944	0.00376	0.00794	0.0108	0.00867	0.00993	0.00530	0.00944	
N	4692	5035	4692	4692	4692	4692	4655	4692	
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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 3](#). 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) we cluster standard errors only on the bank-level. Standard errors (in parentheses) are double-clustered on bank and year level for columns (1)-(7). See [subsection 4.1](#) and [section 3](#) for more details. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Robustness of Executives’ “tech-orientation” to the inclusion of Non-Base Compensation

	NPLs		IT-adoption	
	(1)	(2)	(3)	(4)
Executives’ “tech-orientation”	-0.477*** (0.151)	-0.475*** (0.149)	0.212* (0.114)	0.213* (0.115)
Non-Base Compensation		-0.281 (0.520)		-0.191 (0.665)
R-squared	0.0844	0.0875	0.0241	0.0262
N	80	80	79	79

Results of estimating the following equation:

$$Y_b = \alpha + \beta ExecutiveIT_b + \gamma NonBaseComp_b + \epsilon_b$$

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 1 and 2) or the pre-crisis IT adoption (columns 3 and 4), estimated as described in section 3. The independent variable $ExecutiveIT_b$ 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 5.2 and section 3 for more details. The controls $NonBaseComp_b$ is the average share of non-base compensation over total compensation for top executives in 2007. $NonBaseComp_b$ is excluded in columns (1) and (3). Sample size is kept constant by dropping observations with missing values for any variable. Robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$