Stress Testing Banks' Digital Capabilities: Evidence From the COVID-19 Pandemic*

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Abstract

We study the relationship between banks' IT capabilities and their ability to serve customers during the demand shock for digital banking services generated by the COVID-19 pandemic. Amid mobility restrictions, banks with better IT experience larger reductions in physical branch visits and larger increases in website traffic, implying a larger shift to digital banking. They also exhibit shorter reaction times in mentioning COVID-19 on their websites. Banks with better IT originate more PPP loans, especially in areas with more severe COVID-19 outbreaks, higher levels of internet use, and higher bank competition. They also attract more deposits during the pandemic.

JEL classification: G21, G51, G32, G38

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1 Introduction

A long-running trend has seen banks gradually decrease their reliance on physical branches and move services online, reducing the importance of geographic proximity to customers.[1] As banks have expanded geographically, proximity to bank headquarters has also become less important (Berger and DeYoung, 2006). While it seems clear that information technology plays an important role in facilitating these changes, the evidence on the relationship between bank performance and IT investment is mixed (see, e.g., Berger, 2003; Beccalli, 2007; Koetter and Noth, 2013). The recent rise of fintech lenders has intensified the debate about the competitive advantage that technology can provide in credit analysis (e.g., Berg, Burg, Gombović, and Puri, 2020), wealth management (e.g., D'Acunto, Prabhala, and Rossi, 2019), and ability to address underserved clienteles (e.g., Tang, 2019). Nevertheless, branches still matter, and branch closings can lead to persistent declines in small business lending (Nguyen, 2019) and less competitive loan markets (Bonfim, Nogueira, and Ongena, 2020).

The COVID-19 pandemic represents a unique shock to the demand for digital banking services, driven by a sharp decline in customers' willingness and ability to physically visit bank branches. Large-scale mobility restrictions imposed by state and local governments, as well as the risk of infection, have led to substantial barriers to physical banking. Anecdotal evidence suggests that the use of digital banking has substantially increased during the pandemic.[2] For example, Wells Fargo, one of the largest U.S. banks, reported an 81% increase in the amount of money deposited using a mobile device in April 2020 relative to April 2019 and a 23% surge in customers signing on to digital banking since mid-March 2020.[3] Survey data suggest that banks have generally seen a double-digit rise in first-time online accounts, mobile deposits, mobile payments, and overall usage of online and mobile

[1] See, e.g., Keil and Ongena (2020) and Petersen and Rajan (2002).

[2] See, e.g., The Economist (2020)

[3] *Wells Fargo Stories: Digital banking soars in the COVID-19 pandemic*, available online at: https://stories.wf.com/digital-banking-soars-in-the-covid-19-pandemic/

banking.[4]

In this paper, we use this unexpected, unprecedented demand shock for digital banking services as a "stress test" of banks' digital capabilities and their reliance on branches to serve customers. The sudden increase in the demand for digital banking services has represented a major challenge for many banks' ability to serve their customers. Digital-only customers are historically the ones least satisfied with their bank, and before the pandemic, most customers still relied at least partly on physical branches.[5] As the pandemic forces much of banking services to go digital, we hypothesize that banks with stronger IT capabilities and less reliance on physical branches should emerge as relative winners.

To measure bank IT, we use data from Aberdeen Computer Intelligence Database to construct an *IT index* measuring the presence of technologies useful for remote or virtual work and online communication, such as VPN or voice over internet phone (VoiP). We identify 14 relevant technologies and combine these into a measure of bank IT readiness. We expect that this measure of IT capability captures many relevant dimensions of bank IT in the shift to digital banking. Anecdotal evidence supports this interpretation. For example, *McKinsey & Co* research suggests that digital communication channels are important means of adapting to the COVID-19 demand shock. They write that "during the early days of COVID-19 [...], call volumes grew 29 percent, and waiting times quadrupled" and that "in markets [...] with better digital capability, the rise in call volumes was far less severe than in other markets" (Bensley, Khon, Tan, and Taraporevala, 2020). In robustness checks reported in the Internet Appendix, we complement this index with three additional measures: *IT index (other)*, reflecting all the other technologies that are not included in the main index, *IT staff*, measuring the number of IT staff relative to total employees, and *IT budget*, measuring the IT budget scaled by total employees.

[4]Based on polling research by J.D. Power (https://www.jdpower.com/business/press-releases/2020-us-retail-banking-satisfaction-study) and Ondot Systems (summary by Payments Journal at: https://www.paymentsjournal.com/fis-need-updated-digital-roadmaps-to-reflect-the-rapid-shift-to-digital-banking-during-covid-19/).

[5]Based on J.D. Power (2020).

We begin by analyzing the shift of bank customers from physical branches to online, depending on the bank's IT index value. This analysis is important for our interpretation of the IT index: we would expect banks with better IT to more effectively re-direct customers away from physical visits to online web traffic. It is also important because maintaining critical services digitally is crucial for reducing the *economic* costs of non-pharmaceutical interventions during the pandemic. First, we perform an analysis of the relationship between bank IT and physical branch visits. We measure visits to physical bank branches using aggregated and anonymized mobile phone data from SafeGraph, covering approximately 10% of all mobile devices in the United States. We combine these with data on local mobility restrictions imposed amid the COVID-19 pandemic from Keystone Strategy. We find that banks with stronger IT capabilities experience significantly larger reductions in customer visits to physical branches amid local mobility restrictions, suggesting that better IT enables banks to better serve their customers without the need for face-to-face interaction. With a one-standard-deviation increase in IT index, customer visits during mobility restrictions reduce by over 11% of their within-branch standard deviation.

We then perform a similar analysis, but study instead the visits to the bank's website, using data from AlexaRank. The results mirror those on branch visits: better IT is associated with a significantly larger increase in website traffic at the onset of mobility restrictions. Taken together, these results suggest that banks with better IT infrastructure experience larger shifts from offline to online banking amid local mobility restrictions. The economic magnitude is large: a one standard deviation increase in IT increases the shift from mobility restrictions by 33%.

Complementary to website traffic, we analyze the extent to which our IT index is associated with observable differences in the banks' websites. Using data from BuiltWith, we calculate the number of 'web technologies' present on banks' websites. A web technology can comprise many types, including graphical technologies such as jQuery, web traffic services such as content-delivery networks or the type of web server, security certificates, and much

more. While not all technologies are equally important or useful, a greater number of such technologies is likely to imply greater technological investment and sophistication, and thus should be characteristic of banks with better IT. We show that the IT index is significantly positively correlated with website technologies, even though we do not directly measure these technologies in the index. This suggests that the index captures broader digital capabilities than the relatively narrow set of technologies used to calculate the index values. Second, we study banks' reaction times in mentioning COVID-19 on their website. We find that banks with better IT react significantly faster to the pandemic on their websites. A one-standard-deviation increase in IT index is associated with 1-4 days reduction in reaction time, depending on model specification.

We then focus on banks' ability to serve SME borrowers by investigating small business loans originated under the SBA Paycheck Protection Program (PPP). PPP loans are an ideal laboratory to stress test banks' IT capabilities, as originating loans to more than 5 million small businesses within a few months can be a huge operational challenge to banks, especially during a period when it is costly to involve physical contact in the lending process. In fact, on the very first day when the second round of the PPP loan program was launched, its online application system crashed amid the flood of applications. While Li and Strahan (2020) argue that the PPP loan supply reflects traditional measures of relationship lending, media articles suggest that many SME customers have experienced poor service from their traditional banks and, at least in some cases, ended up switching banks as a result. For example, *The Wall Street Journal* writes that "Of businesses that secured PPP funding, about 28% received their loan from a lender with whom they had no prior relationship or a bank that wasn't their primary one...".[6] We obtain loan-level data from the PPP and study the loan volumes each bank generates in each county, controlling for their historical levels of SME lending.

[6] *The Wall Street Journal: When Their PPP Loans Didn't Come Through, These Businesses Broke Up With Their Banks*, July 31, 2020. Available online: https://www.wsj.com/articles/when-their-ppp-loans-didnt-come-through-these-businesses-broke-up-with-their-banks-11596205736

We perform a bank-county-level analysis to examine how PPP loan origination is affected by the bank's IT capacity. Controlling for bank characteristics as well as the bank's prior activeness in the county (including its ex-ante SME lending and deposits in the county), we find that banks with better IT (measured by a higher IT Index) originate significantly greater amounts of PPP loans during the pandemic. This effect of bank IT is both statistically significant and economically sizeable. A one-standard-deviation increase in IT index is associated with a 21% increase in PPP loan volumes generated. These results are robust to including county fixed effects that control for any unobserved factors that might affect local small business credit demand and quality; the results are also robust to further including bank headquarter-state fixed effects.

One possible concern related to this analysis is that bank IT might be endogenous to SME lending. For example, banks that anticipate larger volumes of SME loan demand may choose to invest more in IT to meet such demand. This concern is mitigated by i) the fact that the COVID-19 shock was, by definition, not anticipated by the banks, and ii) our ability to control for the pre-pandemic SME loan volumes at the bank-county level. To further mitigate such concerns, we perform an instrumental variables analysis, using three different instruments for bank IT. First, we calculate the average IT index of non-bank establishments across locations covered by the bank's branch network, weighting by bank deposits. Second, we calculate a similar non-bank IT index at the bank's headquarter location. Third, we calculate the deposit-weighted number of internet providers using internet access data and branch locations from the year *2010*, a decade before the pandemic. Each of these instruments is likely to capture aspects of the bank's IT quality that are not directly related to its business but rather dictated by the location where it operates. Our baseline PPP loan results are robust to using any of these three instruments, as are our footfall, web traffic and impending results on deposits. Therefore, any alternative explanation must plausibly explain *both* the *time-varying* correlation between bank IT and bank loans, footfall, web traffic, deposits as well as between bank IT and local peer firms' IT and internet availability.

We believe these conditions significantly limit alternative explanations.

We also examine how the importance of IT for loan provision during this period varies across counties with different characteristics. First, if our results are driven by the ability of banks with good IT to better serve customers digitally during the COVID-19 outbreak, we would expect the estimated effect of IT on PPP loan volumes to be larger in areas that experienced worse outbreaks of the virus, as such areas would have experienced the largest shift in demand from physical to digital banking services. Our results support this prediction, with the estimated effect of IT being larger in counties with a higher number of confirmed COVID-19 cases per capita. Second, we find that the effect of bank IT is stronger in areas with greater high-speed internet penetration. This is intuitive, as customers in these areas are more likely to shift to digital banking than in areas with worse internet infrastructure.

Third, we study the effect of local banking competition. In less competitive markets, banks have greater market power and the competitive advantage conferred from superior digital service quality should be less important. In more competitive markets, strong bank IT is likely be more significant for a bank to obtain or retain market share. Accordingly, we find that the effect of IT is larger in areas with lower Herfindahl–Hirschman Index (HHI) of SME loans, suggesting that the number of competitors and the level of concentration matters. We also find that bank IT matters more when competitors have weak IT – likely because in these cases it allows banks to positively differentiate themselves from their competition.

As a final measure of a bank's ability to serve its customers during the crisis, we study the relationship between IT capabilities and deposit growth during the onset of the COVID-19 pandemic. Levine, Lin, Tai, and Xie (2020) show that banks experience large deposit inflows during the first months of the pandemic. We find that banks with stronger IT capabilities experience significantly higher increases in deposits during the first two quarters of 2020. Consistent with anecdotal evidence, this suggests that banks that are better able to serve customers during the pandemic also attract more deposits during the COVID-19 shock, potentially reflecting customers switching their banking relationships. In the Internet

Appendix, we perform an analysis showing that firms are more likely to switch to better-IT banks in areas harder hit by COVID-19, and in cases where their existing lender has worse IT.

We also confirm the robustness of our results by making sure that they are not sensitive to the way we measure bank IT capability. In the Internet Appendix, we show that all our main results are robust to using alternative measures for bank IT. First, the results are robust to measuring bank IT strength using the full set of technologies reported in the Aberdeen database, excluding the ones used in our main IT measure. However, it is worth noting that when both the main IT measure and this alternative measure based on the other technologies are simultaneously included in the regression analysis, the main measure still drives the results, which further corroborates that our main IT measure reflects the technologies that are most relevant to serving customers remotely. Second, the results are robust to measuring bank IT based on its stock of technology labor force, which is estimated by the number of IT staff relative to the total number of employees. Third, the results are also robust to using a bank's investment in technology, which is estimated based on its IT budget per employee.

We make several important contributions. First, we add novel evidence of the impact of technology on bank operations, a topic that has proven elusive in prior literature. Traditionally, it has been difficult to measure IT at the firm level. Moreover, changes customers' preferences toward remote services might occur over a long period. In our study, our measures of banks' IT capabilities are substantially more detailed than most prior studies, and the COVID-19 pandemic represents a unique shock to demand for remote banking services, which allows a better identification of the impact of technology than is possible in normal times. In perhaps the closest prior study to ours, Pierri and Timmer (2020) find evidence that a higher pre-crisis PC adoption by banks is associated with lower levels of non-performing loans during the financial crisis of 2008-2009. However, the focus of that study is different and limited to credit quality, as the financial crisis did not represent a shock to digital

banking demand.

Second, our study is related to the literature on the interplay between between traditional banking and fintech services. Rather than estimating the levels of substitution between banks and fintech lenders, we look at the substitution between banks depending on their digital capabilities, allowing us to assess the fintech readiness of traditional financial institutions. Given the increasingly blurred boundaries between banks and alternative finance providers, this may represent a fruitful direction for future research as well.

Third, we add to the rapidly growing literature on the effects of the COVID-19 pandemic on firms, households, and financial institutions. Our findings suggest that banks differ in their capability to serve customers digitally and suggest that the banking system as a whole may not be fully prepared for the shift toward digital banking. This finding is important in assessing the economic costs of non-pharmaceutical restrictions, as greater substitutability between banks' online and offline services can reduce the economic impact of mobility restrictions.

Finally, our results may have broader implications beyond banking to other industries that are considering the costs and benefits of technology adoption versus expanding its traditional brick-and-mortar presence.

2 Relevant literature

2.1 Banks, technology, and branches

There is a vast literature studying the implications of technological change on banking. Daniel, Longbrake, and Murphy (1973) finds evidence of the use of computers facilitating economies of scale. While several studies focus on the role of IT in bank productivity, the findings are somewhat mixed. Berger (2003) argues that technology in banking has led to improvements in cost efficiency and lending capacity. Beccalli (2007) finds only weak evidence of a link between banks' IT investment and bank performance. Koetter and Noth (2013)

calculate bank productivity estimates adjusting for IT expenditures and find evidence of an upward bias in bank productivity estimates when ignoring banks' IT expenditures. Pierri and Timmer (2020) find evidence that a higher pre-crisis PC adoption by banks is associated with lower levels of non-performing loans during the financial crisis of 2008-2009.

A long-running trend has seen banks gradually decrease their reliance on physical branches and move services online, reducing the effect of distance on lending decisions and enabling banks to serve customers and markets they otherwise could not reach. For example, Petersen and Rajan (2002) find evidence of technology facilitating small business lending to increasingly distant customers. Keil and Ongena (2020) find evidence of technological change as well as bank fragility and consolidation contributing to the decrease in branches. Basten and Ongena (2020) find evidence of banks using online platforms to increase geographic diversification. D'Andrea and Limodio (2020) find that the introduction of high-speed internet promoted private-sector lending by banks, and credit and sales firms. Going much further back in time, Lin, Ma, Sun, and Xu (2020) show that the telegraph enabled Chinese banks to significantly expand their branch networks in terms of both number and geographic scope in 1881-1936. Berger and DeYoung (2006) find that technological progress has facilitated banks' geographic expansion further away from parent banks.

Despite the advances in technology, there is also substantial evidence that branches and physical proximity still matter. Degryse and Ongena (2005) find evidence of spatial price discrimination in bank lending, with loan rates decreasing with the distance between the firm and the lending bank and increasing with the distance between the firm and competing banks. They argue that the observed price differences are caused by transportation costs. Nguyen (2019) shows that branch closings can lead to persistent declines in small business lending. Garmaise and Moskowitz (2006) find that bank presence and competition can also have important social consequences. Neighborhoods that experience a reduction in bank competition via bank mergers are subject to higher interest rates, diminished local construction, lower prices, an influx of poorer households, and higher property crime in

subsequent years. Lin (2020) finds that local stock ownership at bank branch locations affects a customer's propensity to withdraw deposits during stock market booms and affects bank lending.

2.2 Fintech and sources of technological advantage

The rapid rise of fintech lenders and other technology-driven financial institutions has substantially increased the focus on potential competitive advantage that technology can provide. As discussed by Berger and Black (2019), technological changes can increase small business credit supply through the adoption of new hard-information-based lending technologies. Berg et al. (2020) show that technology and the use of easily accessible digital data can substantially improve credit analysis, while Iyer, Khwaja, Luttmer, and Shue (2016) find that peer screening facilitated by peer-to-peer platforms does better than credit scores in predicting defaults. Hertzberg, Liberman, and Paravisini (2018) find that the choice of loan terms on online platforms can be used to screen borrowers based on their private information. D'Acunto et al. (2019) find that robo-advisers can help some clients make better investment decisions. Fuster, Plosser, Schnabl, and Vickery (2019) show that fintech lenders process mortgage applications substantially faster and adjust supply more elastically than other lenders, without incurring higher default costs. On the other hand, technology may not be the only source of competitive advantage for fintech players. Buchak, Matvos, Piskorski, and Seru (2018) argue that a large factor in the rise of fintech lenders is regulatory arbitrage. They estimate that regulation accounts for roughly 60% of shadow bank growth in mortgage lending, while technology accounts for roughly 30%.

While it is commonly argued that fintech firms are able to address underserved clienteles, the evidence on the substitution versus complementarity between fintech firms and traditional financial institutions is mixed. For example, Tang (2019) finds evidence that P2P lending is a substitute for bank lending in terms of serving infra-marginal bank borrowers but complements bank lending with respect to small loans. Danisewicz and Elard (2019)

find that access to fintech credit reduces personal bankruptcies. There is also an ongoing debate on whether removing face-to-face interaction and moving to algorithm-based decision making increases or decreases bias and discrimination in credit decisions. Bartlett, Morse, Stanton, and Wallace (2019) find that fintech algorithms discriminate less against minority borrowers than face-to-face lenders. On the other hand, Fuster, Goldsmith-Pinkham, Ramadorai, and Walther (2020) find that Black and Hispanic borrowers are disproportionately less likely to gain from the introduction of machine learning into credit decisions.

2.3 COVID-19, households, firms, and mobility restrictions

The COVID-19 pandemic has taken hundreds of thousands of lives, strained healthcare systems, and forced shutdowns of large parts of the global economy. In the United States, the rapid increase in local COVID-19 cases in early March sparked large-scale mobility restrictions across many states. These included school closures, bans on gatherings, social distancing orders, and stay-at-home orders (e.g., Adalja, Toner, and Inglesby, 2020).

The onset of the pandemic represented a dramatic negative shock to household consumption (e.g., Baker, Farrokhnia, Meyer, Pagel, and Yannelis, 2020; Andersen, Hansen, Johannesen, and Sheridan, 2020) and the trading conditions of many businesses, resulting in unprecedented numbers of layoffs and business closures within a short time (e.g., Bartik, Bertrand, Cullen, Glaeser, Luca, and Stanton, 2020a; Humphries, Neilson, and Ulyessea, 2020). As a response to the crisis, the U.S. Congress passed The Coronavirus Aid, Relief, and Economic Security (CARES) Act, which included 350 billion dollars to fund the Paycheck Protection Program (PPP). The PPP was designed to support small businesses by extending forgivable loans. Similar schemes of government-guaranteed loans have been adopted in a number of other countries (see, e.g. Alstadsæter, Bjørkheim, Kopczuk, and Økland, 2020; Bennedsen, Larsen, Schmutte, and Scur, 2020; Paaso, Pursiainen, and Torstila, 2020). For larger listed firms, Acharya and Steffen (2020) show that the early stages of the pandemic were associated with extreme precaution, with firms generally drawing down existing bank

credit lines and raising cash holdings. Li, Strahan, and Zhang (2020) also document this shock to liquidity demand on bank balance sheets.

There are a few recent studies focusing on the impact of the pandemic on banks and alternative lenders. Fu and Mishra (2020) find evidence of a significant increase in finance mobile application downloads globally. Erel and Liebersohn (2020) find evidence of fintech players originating more PPP loans in areas with fewer bank branches, lower incomes, and a larger minority share of the population, as well as in industries with little ex-ante small-business lending.

3 Data and methodology

3.1 Measuring IT capability

To measure banks' IT capabilities, we use data from Aberdeen's Computer Intelligence Technology Database. Aberdeen collects data via telephone research interviews. In 2019, the database covered roughly 3.2 million establishments in the United States, including about 85% of all establishments with employment size over 10 and the vast majority of US corporations. We use the Competitive Installs file which identifies 63 major lines of technology installed at each establishment. We identify 14 technologies which are useful for virtual, automated or remote work, falling into the following categories: VPN and remote access, document management, collaborative software, customer relationship management software, video conference and internet phone software, database software and server virtualization. Our *IT index* is calculated as the natural logarithm of the sum of 14 dummies indicating the presence of each of the technologies. We aggregate the index to a bank-level measure by employee-weighting our office-level IT measure.

While our measure has the advantage of parsimony, in practice, software product solutions may vary in quality across vendors or importance for remote work. To mitigate concerns about measurement error, we also show in the Internet Appendix that our analysis is robust

to using alternative IT measures. First, we construct *IT index (other)*, calculated using a similar methodology to the main index, but including instead the remaining technologies that are not included in the main measure. Examples of the remainder of the 63 categories include technologies such as workstations, phone provider, internet providers and generic business categories. Our findings are robust to using this measure as well. However, when including both *IT Index* and *IT Index (other)* in the same regression specification, we find that for all outcomes, *IT Index* remains significant and often dominates the effect of *IT Index (other)*. This suggests that our choice of technologies is meaningful. Second, we measure *IT staff*, calculated as the number of IT staff, divided by total employees, for each bank. We note that our measure of IT staff is inexact as Aberdeen reports ranges of employees rather than exact counts (e.g. 1-4 employees, 250-499), which we impute at the midpoint. Third, we measure *IT budget*, calculated as the natural logarithm of total IT budget, divided by total employees, for each bank. While these last two measures provide valuable robustness checks, we prefer our simple count-based measures because they allow us to isolate those technology investments particularly useful for remote work. Moreover, more so than the amount spent, we argue it is the *breadth* of capabilities that is relevant (e.g. a very expensive VPN is less useful than a suite of software services such as VPN, internet phones and video conferencing software) for adapting business processes in a remote context.

Finally, we construct three different instrumental variables to capture exogenous variation of IT capabilities across banks. Our first instrument is based on the idea that IT capacities of non-bank establishments in a location can affect the banks' IT adoption in the same place. Specifically, we first compute the average IT index (based on the same measure that we do for banks) of non-bank establishments in a zip code and then, for each bank, we calculate the average non-bank IT across all zip codes where the bank operates, weighted by the bank's deposits in each zip code. Our second instrument focuses on the non-bank IT index of the zip code where the bank's headquarter is located. Our third instrument is based on the idea that banks operating in locations with better internet infrastructure are more likely to invest

in IT to better service their customers. As such investment take place over time, this last instrument calculates the weighted-average number of internet providers in 2010 across the bank's branch network.

3.2 Measuring physical branch visits

To measure customer visits to bank branches, we use aggregated mobile phone data from SafeGraph, a company producing anonymized mobile phone location statistics covering 10% of U.S. mobile devices. The data include monthly number of visits at each outlet, including bank branches. We perform a name-based matching of SafeGraph data to FDIC Summary of Deposits (SOD) dataset to obtain branch details and to aggregate branches at bank level. We are able to match 56,242 branches out of the total 86,367 branches in the SOD data. Matching this further to Aberdeen at the establishment level yields a sample of 32,146 branches for which we can study IT and footfall. We then construct a monthly panel dataset of physical branch visits at the branch level and further aggregate that to bank-county and bank level.

SafeGraph observes 18.75 million devices, approximately 5.6% of the U.S. population and about 10% of mobile devices. According to SafeGraph's analysis of user characteristics, SafeGraph posits that its sample is representative of the U.S. population based on its own study of income characteristics, age, and demographics of its users. The data are widely used in studies of social distancing during the COVID-19 pandemic.

3.3 Measuring online traffic to banks

We also examine the websites of banks, for which there is ample data on their historical composition as well as web traffic. One may wonder if firms with better technology were able to respond more quickly to COVID-19 through their online portals, which might be used to serve customers. We combine data from several sources. For online traffic, we obtain data from Censys, a cybersecurity firm that monitors the AlexaRank top 1 million websites. We

have 1,516 websites in the AlexaRank top 1 million in our sample which we can observe on a weekly basis. Given that the AlexaRank captures the relative standing of banks' websites throughout this time, we expect that banks with better IT may achieve a better ranking in AlexaRank – as demand for their online services grows, the firms with better IT are more capable of serving a boon in customer demand.

We obtain data on the *historical* composition of firms' websites through BuiltWith, which indexes site technologies over time. We obtain data from their Domains API, which provides technologies for every subdomain observed on a site. For example, they can measure the existence of jQuery, which is a technology used to implement modern, advanced functionality and user layouts for web pages. IIS, Nginx and Apache are competing types of web servers. Importantly for our purposes, BuiltWith provides a database of the mentions of COVID-19 throughout different websites over time. This allows us to measure different banks' reaction time to the COVID-19 pandemic on their websites. However small or large, we interpret an earlier website mention of COVID-19 as a response of the organization through its website.

3.4 Lending during the pandemic

To measure banks' small business lending during the COVID-19 pandemic, we obtain loan level data from the SBA Paycheck Protection Program. This program, established by the CARES Act, is implemented by the Small Business Administration with support from the Department of the Treasury. This program provides small businesses with funds to pay up to 8 weeks of payroll costs including benefits. Funds can also be used to pay interest on mortgages, rent, and utilities. The program was launched in April 3, 2020 and closed on August 8, 2020.

Our dataset covers the period from the beginning of the program through the end of June, which is the original deadline of the program and the time by which the program was effectively over - by June, banks had conducted over 99% of lifetime PPP lending. We construct a bank-county level dataset of PPP loans during this period. To assess the volume

of PPP loans relative to the SME lending done by the bank in normal times, we control for the ex-ante SME lending volume measured as the total CRA small business lending by the same bank to the same county in 2018. [7] In addition, we also control for the level of deposits to the same bank in the same county (estimated based on the 2019 SOD data), which can be another proxy for each bank's activeness in each county.

We also measure bank financial characteristics using the call report data, including bank deposits, size (measured by total assets), capitalisation (measured by both equity/asset ratio and tier-1 capital ratio), profitability (measured by return on assets (ROA) and cost/income ratio), funding cost, personnel costs, and the number of states where the bank operates.

3.5 Mobility restrictions due to COVID-19

We obtain county-level data on mobility restrictions from Keystone Strategy, available via GitHub. This set of non-pharmaceutical interventions (NPIs) data is collected by hand with reference to government health websites and local news media reports. NPIs are classified into eight different types: closing of public venues, ban on gatherings, lockdowns, non-essential services closures, school closures, shelter-in-place orders, social distancing orders, and other restrictions. To obtain an aggregate measure of the level of restrictions in place at each location, we calculate an index variable *Restrictions* by summing up the number of restriction types currently in force. The possible variable values range from zero (no restrictions) to eight (all restriction types in force).

4 Main results

4.1 Branch visits, mobility restrictions, and bank IT

We start by studying the relationship between bank IT and visits to physical branches during the COVID-19 pandemic. In Figure 1, we plot the average weekly number of visits

[7] This is the latest year of which is CRA data is released.

to bank branches for banks with high, medium and low IT index values over time. We study February 1 to April 30th, to focus on a narrow window before and after the onset of the pandemic in the United States.[8] We see that, following the introduction of mobility restrictions, there is a clear divergence between high-IT and low-IT banks, with branch visits decreasing substantially more for the high-IT banks. This is consistent with the notion that banks with better technology are better able to serve their customers remotely, without requiring face-to-face interaction.

To more formally test for the impact of mobility restrictions on branch visits, conditional on bank IT, we perform a regression analysis of the following form:

$$ln(Branch\,visits)_{i,t} = \alpha_{0,i} + \alpha_1 \times Restrictions_{c,t} \times IT\,index_j + \alpha_2 \times Restrictions_{c,t} + \beta \times X_{i,t} + \epsilon_{i,t} \tag{1}$$

where *Branch visits* is the weekly number of visits at branch i, *Restrictions* is a dummy taking the value one if one or more mobility restrictions are currently in place in county c where the branch is located, at week t, *IT index* measures the IT capabilities of bank j that owns the branch, and X is a vector of controls. We include branch fixed effects ($\alpha_{0,i}$) and, depending on specification, also date fixed effects and state-date fixed effects. We also perform the same analysis using the number of different restriction types, taking values from zero to eight, to measure the level of mobility restrictions.

The results are shown in Table 2. Banks with higher IT index values experience significantly larger reductions in branch visits following the introduction of mobility restrictions by local governments. In column 1, the economic magnitude is such that a standard deviation increase in *IT Index* is associated with an 11% larger reduction in branch visits. This result is statistically significant and robust to various model specifications. Supplementing the graphical analysis, we also test the parallel trends assumption formally. Our analysis

[8]Extending the window yields qualitatively similar results, although we are less confident the Keystone Strategy list comprehensively captures loosening of mobility restrictions. We are also aware that there may be additional confounding events after the initial onset of the pandemic. Therefore, we keep this window relatively short.

suggests that IT facilitates the move from physical branch banking when mobility restrictions arrive. This suggests that we should expect to find a null result the week before the restrictions. The results shown in columns 2 and 5 are consistent with this prediction.

4.2 Website traffic and reaction time to COVID-19

Complementarily, we examine data on websites of the firms. We measure two margins of response. First, we examine the digital analogue of footfall: firms' website traffic. Second, we examine the cross-section of firms' IT and the implications for firm websites.

In columns 1-4, we examine the impact of IT on *web* traffic. We conduct this analysis at the weekly level. We obtain daily AlexaRank data for all banks in our sample. AlexaRank does not include daily counts of web traffic for those firms falling below a threshold, even if the website is in the AlexaRank top 1 million. When we require those who have at least 60 days of coverage during our sample period, this filter leaves us with 414 banks whose main internet portal we could reliably track throughout the sample period, which is the same as above. We caution the reader that even with this filter, we do not have continuous daily coverage for our sample - but our analysis is valid so long as *mobility restrictions* are not correlated with coverage in AlexaRank. Conceptually, the two seem so distant that we believe this assumption should be plausible.

In columns 1 and 2, we show the baseline relation between restrictions and online activity. Column 1 removes bank IT, while column 2 interacts bank IT with restrictions. It shows that after restrictions come into place where the banks operate, banks with better IT increase in AlexaRank relative to those firms with less good IT. This suggests when demand for online services increases that banks with high quality IT gain on a relative basis. Columns 3 and 4 test the parallel trends assumption, again finding evidence of an improvement that coincides with the onset of restrictions, and not before. Column 5 and 6 examine the response time toward COVID-19 as implied by bank websites. In Columns 5 and 6, we report the within-state and within-county relations of IT to the number of technologies observed on a website.

This is a crude proxy and provides no guarantee that IT was useful in a firms' response to COVID-19. Thus, we next examine the earliness of a firms mentioning COVID-19 on their website. In column 3, we find that firms which have better IT mentioned COVID-19 an average of 1.462 days earlier per unit of the IT index. A one-standard-deviation increase in the IT index of 1.7 therefore equates to a 20% quicker response relative to the model residual standard error of 9.54. Column 4 applies a county fixed effect. Relative to the residual standard error, the magnitude enlarges to 33%. This provides suggestive evidence that firms which have better IT respond more quickly to the pandemic.

4.3 Bank IT and PPP lending

4.3.1 PPP loan volumes

We then focus on small business loans originated under the SBA Paycheck Protection Program (PPP). We calculate the total volume of PPP loans originated in each county by each bank. To test for the effect of bank IT on PPP loan origination volume, we first perform the following regression analysis:

$$PPP_{i,c} = \alpha_c + \alpha_{hq} + \alpha_1 \times IT\ index_i + \beta_1 \times X_{i,c} + \beta_2 \times X_i + \epsilon_{i,c} \tag{2}$$

where $PPP_{i,c}$ is the log volume of PPP loans originated by bank i in county c. $X_{i,c}$ is a vector of bank-county level controls, including the log amount of CRA small business lending by the same bank in the same county in 2018 and the log level of deposits to branches of the same banks in the same county in 2019. X_i is a vector of bank characteristics, including the log bank size (measured by total assets), capitalisation (measured by both equity/asset ratio and tier-1 capital ratio), profitability (measured by return on assets (ROA) and cost/income ratio), funding cost, personnel costs, and the number of states the bank operates in. α_c refers to the county fixed effects, and α_{hq} refers to the fixed effects of the bank headquarter states. It should be noted that by controlling for county fixed effects, we are comparing PPP

lending by strong- and weak-IT banks within the same location. This empirical strategy effectively controls for the potential demand effects driven by local economic or pandemic conditions, allowing us to focus on the supply side.

The results are shown in Table 5. Across all the specifications, a stronger bank IT, as measured by a higher IT Index, is related to a significantly larger amount of PPP lending during the pandemic. This result is robust when controlling for the ex-ante SME lending as well as deposits of the same bank to the same county. It is also robust when controlling for the county fixed effects (which pin down all unobserved variations in local credit demand and quality) as well as the bank headquarter fixed effects. The effect is also economically significant: according to the point estimate in column 4, a one-standard-deviation increase in bank IT leads to a 21% increase in PPP lending to small businesses.

4.3.2 Instrumental variables analysis

Since our results on PPP lending to SMEs are based on a comparison across different banks' IT capacities, one possible concern is that bank IT might be endogenous to other factors that affect SME lending. For example, banks that anticipate larger volumes of SME loan demand may choose to invest more in IT to meet such demand. This concern is mitigated by i) the fact that the COVID-19 shock was, by definition, not anticipated by the banks, and ii) our ability to control for the pre-pandemic SME loan volumes at the bank-county level and a vector of bank characteristics that are typically considered to determine bank financial status and lending activities. To further mitigate such concerns, we perform a set of instrumental variables analyses using three different instruments for bank IT, including the weighted-average non-bank IT index across the bank branch network, non-bank IT index at the bank's headquarter, as well as the weighted-average number of internet providers in 2010 across the bank's branch network. The first-stage regression results are reported in Table A.1 in the Internet Appendix. They show that, controlling for other bank characteristics, all three instruments strongly explain the cross-bank variation of IT.

Table 6 reports the second stage IV regression results. The positive effect of bank IT on PPP lending to SMEs during the pandemic remains robust when estimated based on more exogenous variation in bank IT as captured by each of these three instruments. Our other baseline analyses are also robust to using a similar IV analysis, as shown in the Internet Appendix.

4.3.3 Differential effects of IT across counties

If our results are driven by the ability of banks with good IT to better serve customers digitally during the COVID-19 outbreak, we might expect the estimated effect of IT on PPP loan volumes to be larger in areas that experienced worse outbreaks of the virus. To test this prediction, we study the impact of bank IT conditional on the severity of the likely demand shock caused by the outbreak. We perform a regression analysis including an interaction between the IT index and the number of confirmed COVID-19 cases in the county. The results are shown in the first two columns of Panel A of Table 7. The estimated effect of IT is larger in counties with a higher number of confirmed COVID-19 cases per capita.

We then explore the importance of local market characteristics in the role of bank IT. We first study the level of internet use, measured by the share of households with access to broadband internet, as a proxy for customers' propensity to use, and differentiate between, banks' online services. The results, shown in columns 3 and 4 of Panel A of Table 7, suggest that bank IT matters more when the customer base has better internet infrastructure. This is intuitive, as customers in these areas are more likely to shift to digital banking than in areas with low internet use.

Finally, we study how the role of bank IT varies across locations with different levels of banking competition. As a measure of market concentration, we calculate the Herfindahl–Hirschman Index (HHI) of SME loans in the county before the pandemic. In addition, we also measure the quality of competition by calculating the average IT strength of the peer banks that compete in the same county. The results, shown in Panel B of Table 7, suggest

that both the quantity and the quality of competition matter. First, columns 1 and 2 show that the effect of IT index on PPP loan volumes is higher when the market concentration is lower (as measured by a lower HHI index), suggesting that a strong IT capability is more valuable to a bank when it faces greater competition in a local market. Second, columns 3 and 4 show that a stronger IT capability matters more when competitors have weaker IT. This suggests that IT matters the most when it allows the bank to positively differentiate itself from competitors.

It is worth noting that all these differential effects are qualitatively and quantitatively similar when we make the comparisons within the same county and bank: controlling for both the county and bank fixed effects, we find that, even for the same bank, a stronger IT capability can have a stronger effect on PPP lending in counties with greater demand shock, with better internet, and with greater banking competition or weaker competitor IT. These within-bank comparisons also help us further rule out the concern that our results are driven by unobserved bank characteristics that are correlated with bank IT.

4.4 Bank IT and deposits

We also look into the dynamic growth of bank deposit over the first two quarters of 2020 as another measure a bank's ability to serve its customers during the crisis. Using quarterly bank-level data from call reports, we run the following panel analysis to estimate the role of bank IT in their ability to attract deposits:

$$\begin{aligned}\Delta ln(Deposits)_{i,t} =& \alpha_i + \alpha_t + \gamma_1 \times IT\ index_i \times (Year_t = 2020) + \\ & \gamma_2 \times IT\ index_i \times (Quarter_t = 2019Q4) + \beta \times X_{i,t-1} + \epsilon_{it}\end{aligned} \tag{3}$$

where $\Delta ln(Deposits)$ is the change in the deposits of bank i in a logarithmic form, measuring a relative change. α_i and α_t are the bank and quarter fixed effects. $(Year_t = 2020)$ is a dummy variable that equals to one for the first two quarters in 2020 (where the pandemic is going on) and 0 otherwise. $(Quarter_t = 2019Q4)$ is a dummy variable that equals to one for

2019Q4 and 0 otherwise, which controls for the potential pre-shock trending effects. $X_{i,t-1}$ is a vector of lagged controls, including bank size (measured by total assets), capitalisation (measured by both equity/asset ratio and tier-1 capital ratio), profitability (measured by return on assets (ROA) and cost/income ratio), funding cost, and personnel costs.

The results are shown in Table 8. We can see that a stronger bank IT capacity is related to a significantly higher deposit growth, and this effect is robust to controlling for other bank characteristics and the pre-shock trend.

5 Additional analysis and robustness checks

5.1 Alternative IT measures

Besides addressing the potential endogeneity concerns using the instrumental variable analysis, In Internet Appendix Section A.2, we also confirm the robustness of all our results by showing that they are not sensitive to the way we measure bank IT. In particular, we find that all our main results are robust to using three alternative measures of bank IT.

First, our results remain robust when we measure bank IT using all the other technologies (*IT index (other)*) that are not included in the main IT measure. However, it should be noted that when both the main IT measure and this alternative measure of other technologies are simultaneously included in the regression analyses, our main measure is stronger in nearly all analyseses, which further corroborates that our main IT index reflects the technologies that are most relevant to serving customers remotely. Second, our results remain similar when we measure bank IT using *IT staff*, the number of IT staff relative to the total number of employment, which reflects a bank's stock of technology labor force. Finally, our results are also robust to measuring bank IT using *IT budget*, the log amount of IT budget per employee, which reflects a bank's financial investment in technology.

5.2 Likelihood of switching banks

In Internet Appendix Section A.2, we study firms' propensity to switch banks when obtaining a PPP loan. Under our main hypothesis that a stronger IT helps a bank to attract customers from its peer banks, customers are expected to switch from weaker-IT banks to stronger-IT ones in response to the pandemic. Instead, under an alternative hypothesis that ex-ante differences in clientele lead to differential responses to the pandemic, any such switching behavior should be unrelated to bank IT. We test these hypotheses by matching borrowers in the previous SBA 7a programs and the PPP program, forming a panel of 28,593 firms who made borrowings in both.

We conduct this analysis with a dummy outcome variable that equals 1 if the borrower switches to a bank with better IT (i.e. if the lender in the PPP program has better IT than the lender in the previous SBA 7a program for this same borrower). Our baseline hypothesis suggests that in areas more afflicted by the pandemic, where the demand shock is greater, firms will be more likely to switch to a bank with better IT. Our findings confirm this hypothesis. Controlling for lender fixed effects for the SBA loan program (which controls for potential client selection) and borrower industry fixed effects (which controls for the firm's inherent demand for credit), we find that the borrower is more likely to switch to a bank with better IT if it is in a county more affected by the pandemic. This finding remains robust under different measures of IT, including *IT index*, *IT budget* and *IT staff*.

5.3 Discussion of alternative interpretations

One potential concern is that we might not be capturing the impact of IT but rather of a characteristic that IT is highly correlated with. Of course, technological sophistication may be only one component of a bank's response to COVID-19, which might also include other operational aspects, human resource practices, corporate governance, or other features. But it is hard to imagine a characteristic that would be so highly correlated with technological sophistication that it would render technological sophistication itself wholly irrelevant.

Technological capabilities should be paramount when human interactions are restricted, and particularly when considering website traffic as the outcome variable.

Such characteristic would have to match the timing of mobility restrictions in a county in its effect on physical branch banking and on website traffic. It would also have to explain the bank's ability to respond to COVID-19 on its website. Given we are controlling for county and bank fixed effects, such characteristic would also have to explain the bank's ability to lend in high-internet counties, be correlated with information and internet technology, but not be IT itself. Finally, in light of our instrumental variables analysis, such characteristic would also have to be correlated with local IT of firms not in the banking industry or increases in local internet speed.

In particular, our bank-level outcomes such as PPP and deposit growth are not likely to be driven by bank size. In these regressions, bank size is actually *negatively* related to the outcome variables. Moreover, contemporaneous studies on PPP loans suggest that larger banks have actually not engaged heavily in PPP loans as it is less worthwhile for large banks to allocate attention to processing loans for clients they would not typically serve Bartik, Cullen, Edward L. Glaeser, and Sunderam (2020b).

Finally, our study is a test of the idea that IT helps banks capture demand shocks for digital services. One might wonder if there is a differential demand shock among clients of high-IT and low-IT banks or reflective of new customers. That is, it is possible that clients of good IT banks are more sensitive to social distancing guidelines, more likely to apply for PPP loans and have better economic outcomes during the pandemic. We believe this alternative explanation is unlikely to drive our main findings, particularly the results based on within-bank analysis on PPP lending. It also does not explain the response by better IT banks on their website or why remote technologies for internal use within the bank seem more relevant to consumer than other technologies the firm possesses. Finally, it is not consistent with our findings on the likelihood of switching to better-IT bank being driven by local COVID-19 situation.

6 Conclusion

We find convincing evidence that banks' IT capabilities affect their ability to serve customers during the COVID-19 pandemic. While the COVID-19 outbreak represents an unprecedented demand shock for digital banking services, our findings have broader implications beyond the pandemic, as they suggest a general negative relationship between technology and reliance on physical branches.

It is not yet clear to what extent the demand for physical branch banking will return once the threat of infection decreases. However, given there was already a long-running trend toward reduced reliance on branches and increasingly digital banking services, it seems likely that investment in improving IT capabilities may help to both better position banks for the future, as well as to reduce their vulnerability to extreme shocks such as the COVID-19 pandemic. The latter point might also have important implications for the stability of the financial system more broadly. That a relationship between IT and banking activity exists today suggests variation among banks in the ability to provision credit digitally – and less than complete readiness in the U.S. banking sector.

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Figure 1: Branch Visits vs. Bank IT

Average weekly number of customer visits to physical bank branches, divided into banks with high vs. low IT index.

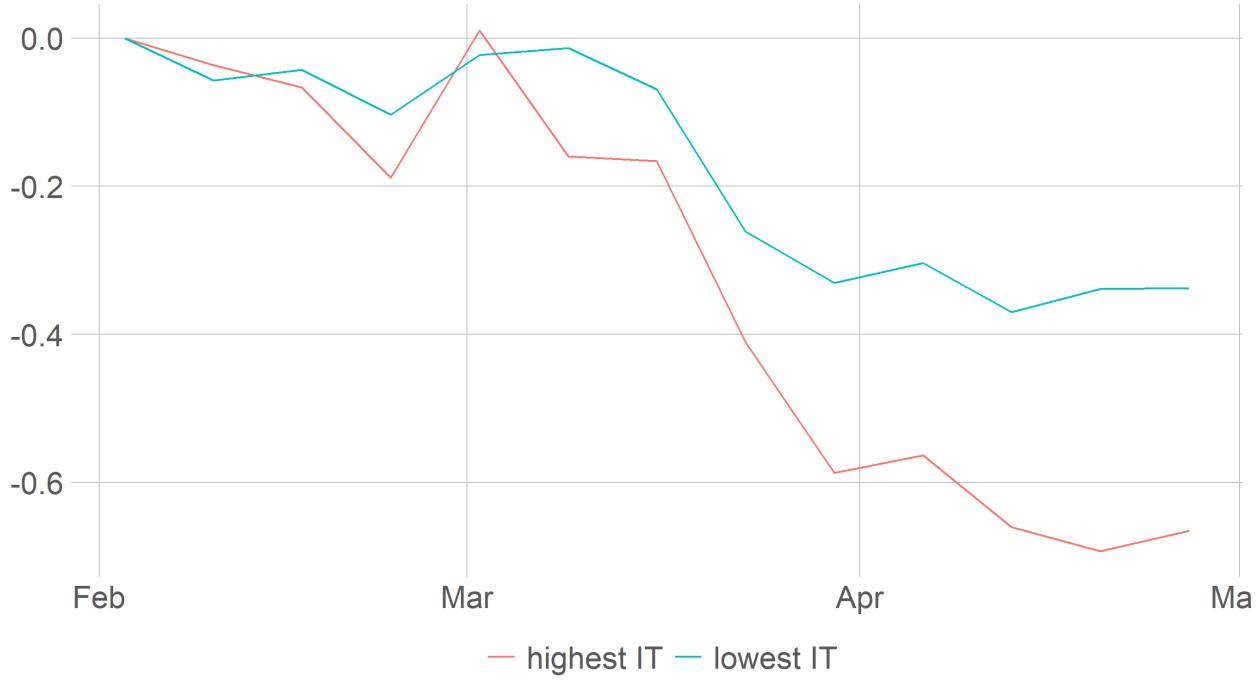

Table 1
Summary statistics

This table reports the summary statistics of our samples for different analyses.

	N	Mean	Std	p25	p50	p75
Bank level						
IT index	2,590	1.045	0.395	0.693	1.076	1.304
IT index (other)	2,590	1.875	0.379	1.615	1.902	2.082
IT staff	2,590	0.126	0.055	0.093	0.122	0.161
IT budget	2,590	10.603	0.641	10.265	10.617	10.961
# Website Techs	3,196	91.960	96.823	44.000	71.000	106.000
ln(# Website Techs)	3,196	4.268	0.679	3.806	4.276	4.672
Response Time	3,196	72.109	24.66365	66.000	66.000	72.000
Bank-Quarter level						
Δ ln(Deposits)	14,466	0.029	0.066	-0.005	0.017	0.047
ln(Total assets)	14,466	13.319	1.419	12.303	13.007	13.976
Equity/Assets	14,466	11.471	2.415	9.745	11.017	12.727
Tier 1 ratio	13,631	15.367	4.833	12.089	13.895	16.976
RoA	14,466	0.603	0.432	0.273	0.485	0.853
Cost/Income	14,463	65.960	12.083	57.801	65.661	73.860
Funding cost	14,466	0.467	0.329	0.214	0.363	0.655
Personnel costs	14,463	38.066	7.917	32.900	37.996	43.149
N states	14,466	3.976	8.325	1.000	1.000	2.000
Bank-Week level						
ln(Alexarank-10^6)	3,607	12.622	3.416	13.331	13.559	13.706
Alexarank-10^6	3,607	727044.551	249549.252	615963.5	773939	896149
Branch-Week level						
Branch visits	386,236	14.918	34.037	3.000	8.000	18.000
Bank-County level						
PPP loans (USDm)	28,881	10.688	43.489	0.120	0.845	5.004
CRA	28,881	5.914	23.853	0.250	0.970	3.549
Deposits	28,881	266.372	3,605.152	0	0	62.165

Table 2
Branch Visits During Mobility Restrictions vs. Bank IT

This table tests the impact of mobility restrictions on branch visits for banks during the COVID-19 pandemic. The unit of observation is a branch-week. The dependent variable, *ln(Branch visits)* is the number of visits recorded in Safegraph's Places of Interest file. *Restr.* is a dummy indicating that there are mobility restrictions in place in the country. *Num. Restr.* is an index counting the number of mobility restrictions in place at the county-level, taking values from zero (no restrictions) to eight (all restrictrion types in place). The sample period is February 1, 2020 to April 30, 2020. Robust standard errors clustered by county are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
IT index x Restr.	-0.0766***	-0.0809***	-0.0648***			
	(0.0115)	(0.0160)	(0.0109)			
IT index x Restr. (t-1)		0.0043				
		(0.0119)				
Restr.	-0.0100	0.0034	-0.3327***			
	(0.0114)	(0.0146)	(0.0252)			
Restr. (t-1)		-0.0182				
		(0.0151)				
IT index x Num. Restr.				-0.0171***	-0.0162***	-0.0124***
				(0.0027)	(0.0037)	(0.0024)
IT index x Num. Restr (t-1)					-0.0009	
					(0.0027)	
Num. Restr.				-0.0093***	-0.0114***	-0.0875***
				(0.0033)	(0.0030)	(0.0048)
Num. Restr. (t-1)					0.0027	
					(0.0030)	
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Date FE	No	No	Yes	No	No	Yes
N	386,236	386,236	386,236	386,236	386,236	386,236
R^2	0.8517	0.8517	0.8465	0.8518	0.8518	0.8505

Table 3
Website Traffic During Mobility Restrictions vs. Bank IT

In this table, we test the impact of mobility restrictions on a firm's AlexaRank, a proxy for website visitations, for banks during the COVID-19 pandemic. The unit of observation is a firm-week. The dependent variable is *Online Traffic* which is defined as $log(10^6 - Alexarank)$, scaled so higher values equal higehr web traffic. AlexaRank is the website's weekly Alexarank recorded in Censys, a cybersecurity dataset.*Restr.* is a dummy indicating that there are mobility restrictions in place in the country. *Num. Restr.* is an index counting the number of mobility restrictions in place at the county-level, taking values from zero (no restrictions) to eight (all restrictrion types in place). The sample period is February 1, 2020 to April 30, 2020. Robust standard errors clustered by bank are reported in parentheses.

	(1)	(2)	(3)	(4)
IT index x Restr.	0.8651***	0.7783***		
	(0.1197)	(0.1453)		
IT index x Restr. (t-1)		-0.1515		
		(0.1100)		
Restr.	-0.7042***	-0.7037***		
	(0.1412)	(0.1351)		
Restr. (t-1)		0.7076***		
		(0.1287)		
IT index x Num Restr.			0.3016***	0.2561***
			(0.0396)	(0.0591)
IT index x Num Restr. (t-1)				-0.0344
				(0.0497)
Num Restr.			0.0821	0.0186
			(0.1199)	(0.1241)
Num Restr. (t+1)				0.2295***
				(0.0505)
Bank FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
N	3,607	3,513	3,607	3,513
R^2	0.5830	0.5785	0.5839	0.5793

Table 4
Website Characteristics and COVID-19 Response Time

In this table, we characterize the relation between our measures of IT and website characteristics. The dependent variable is shown above each column. *Website Techs* is the number of observed BuiltWith technologies by February 2020. *Response time* is the number of days from the first US COVID-19 case that it took for the bank to mention COVID-19 on its website. Negative coefficients imply earlier responses. Robust standard errors clustered by bank are reported in parentheses.

	ln(1+#Website Techs)		Response time	
	(1)	(2)	(3)	(4)
IT index	0.9026***	0.6031***	-8.7035***	-3.6402***
	(0.0328)	(0.0210)	(0.9300)	(1.1240)
Bank controls	No	Yes	No	Yes
State FE	Yes	Yes	Yes	Yes
N	3,196	3,162	3,196	3,162
R^2	0.4928	0.5893	0.0725	0.1038

Table 5
Bank IT Strength and PPP Lending During the Pandemic

The dependent varible is *ln(PPP loans)*, the bank-county level log amount of PPP loans originated. *ln(CRA loans)* is the natural logarithm of the total amount of CRA small business lending in 2018 by the same bank to the same county. *ln(Deposits)* is the natural logarithm of deposits to the same bank from the same county as reported in the 2019 branch-level SOD data. Heteroskedasticity-robust standard errors clustered by county and bank are reported in parentheses.

	(1)	(2)	(3)	(4)
IT index	0.4763***	0.6463***	0.4761***	0.5247***
	(0.1712)	(0.1842)	(0.1406)	(0.1193)
ln(CRA loans)		0.5109***	0.4041***	0.4343***
		(0.0236)	(0.0269)	(0.0189)
ln(Deposits)		0.4001***	0.4279***	0.4083***
		(0.0169)	(0.0154)	(0.0131)
ln(Total assets)	0.0156	-0.2283**	-0.1808**	-0.1629***
	(0.0760)	(0.1086)	(0.0847)	(0.0490)
Equity/Assets	0.0555**	0.0384	0.0430*	0.0436**
	(0.0252)	(0.0292)	(0.0257)	(0.0211)
Tier 1 ratio	-0.0737**	-0.0900***	-0.0987***	-0.0821***
	(0.0319)	(0.0347)	(0.0288)	(0.0207)
RoA	-2.9018**	-1.3268*	-1.5392**	-1.0969**
	(1.2522)	(0.7093)	(0.6606)	(0.5098)
Cost/Income	-0.0292*	-0.0014	-0.0107	-0.0040
	(0.0149)	(0.0107)	(0.0092)	(0.0090)
Funding cost	-1.2754	-0.5778	-1.6458**	-0.6693
	(0.8693)	(0.7552)	(0.7432)	(0.7403)
Personnel costs	0.0041	-0.0212	-0.0086	-0.0083
	(0.0175)	(0.0210)	(0.0161)	(0.0122)
N states	-0.0283***	-0.0060	-0.0075	-0.0092**
	(0.0054)	(0.0052)	(0.0047)	(0.0040)
County FE	No	No	Yes	Yes
HQ State FE	No	No	No	Yes
N	28,145	28,145	27,873	27,873
R^2	0.047	0.584	0.660	0.682

Table 6
Bank IT Strength and PPP Lending During the Pandemic (IV)

This table shows the second stage results of an instrumental variable analysis using three alternative instruments for IT index. The dependent varible is *ln(PPP loans)*, the bank-county-level log amount of PPP loans originated. The three alternative instruments are *Non-bank IT (dep.-w.)*, the average non-bank IT index across establishments in the zip codes covered by the bank's branch network, weighted by deposits, *Non-bank IT (HQ)*, the average non-bank IT index at the bank's headquarter zip code, and *N internet providers*, the deposit-weighted number of internet providers in 2010 across the bank's branch network that year. First-stage results are reported in the Internet Appendix. Heteroskedasticity-robust standard errors clustered by county and bank are reported in parentheses.

	Non-bank IT (dep.-w.)	Non-bank IT (HQ)	N internet providers
	(1)	(2)	(3)
IT index	2.2141***	0.9700**	1.7106**
	(0.5900)	(0.4795)	(0.7485)
ln(CRA loans)	0.4471***	0.4386***	0.4420***
	(0.0199)	(0.0194)	(0.0198)
ln(Deposits)	0.4052***	0.4062***	0.4074***
	(0.0134)	(0.0130)	(0.0132)
ln(Total assets)	-0.4747***	-0.2414**	-0.3855***
	(0.1185)	(0.0992)	(0.1488)
Equity/Assets	0.0571***	0.0468**	0.0528***
	(0.0205)	(0.0198)	(0.0195)
Tier 1 ratio	-0.0402	-0.0700***	-0.0534**
	(0.0263)	(0.0234)	(0.0264)
RoA	-1.8445***	-1.2795**	-1.7397**
	(0.6493)	(0.5529)	(0.6944)
Cost/Income	-0.0197*	-0.0074	-0.0148
	(0.0109)	(0.0096)	(0.0113)
Funding cost	-0.2735	-0.5732	-0.4805
	(0.6310)	(0.7005)	(0.6438)
Personnel costs	-0.0012	-0.0074	-0.0046
	(0.0118)	(0.0119)	(0.0113)
N states	-0.0137***	-0.0109***	-0.0120***
	(0.0047)	(0.0041)	(0.0043)
County FE	Yes	Yes	Yes
HQ State FE	Yes	Yes	Yes
N	27,873	27,572	27,714
R^2	0.544	0.572	0.560
F statistic (1st stage)	27.095	16.435	9.598

Table 7
The Differential Effects of Bank IT across Counties

The dependent varible is *ln(PPP loans)*, the bank-county level amount of PPP loans originated. *ln(COVID)* is the natural logarithm of the number of total confirmed COVID-19 cases per 1,000 people in the county until June 30, 2020. *Internet use* is the percentage of households having access to high-speed internet. *HHI* is the Herfindahl-Hirshman Index of SME lending in the county. *HHI* is the average IT index of other banks in the county. Heteroskedasticity-robust standard errors clustered by county and bank are reported in parentheses.

Panel A: COVID-19 cases and internet use

	(1)	(2)	(3)	(4)
IT index x ln(COVID)	0.1038***	0.0768**		
	(0.0328)	(0.0321)		
IT index x Internet use			1.1103***	0.8471***
			(0.2489)	(0.2456)
IT index	0.4975***		0.4758***	
	(0.1176)		(0.1143)	
Bank controls	Yes	No	Yes	No
Bank-county controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
HQ State FE	Yes	No	Yes	No
Bank FE	No	Yes	No	Yes
N	27,873	27,869	25,540	25,537
R^2	0.682	0.717	0.680	0.715

Panel B: County-level competition

	(1)	(2)	(3)	(4)
IT index x HHI	-1.6876***	-1.3119***		
	(0.3705)	(0.3439)		
IT index x Competitor IT			-5.4039***	-5.6038***
			(1.2774)	(1.1330)
IT index	0.4474***		0.4170***	
	(0.1162)		(0.1180)	
Bank controls	Yes	No	Yes	No
Bank-county controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
HQ State FE	Yes	No	Yes	No
Bank FE	No	Yes	No	Yes
N	27,873	27,869	27,873	27,869
R^2	0.682	0.717	0.683	0.718

Table 8
Bank IT Strength and Deposit Growth During the Pandemic

The dependent variable is Δ *ln(Deposits)*, the quarterly bank-level deposit growth. *Year 2020* is a dummy variable that equals one for the first or second quarter of 2020 and zero otherwise. *Q4 2019* is a dummy variable that equals one for the last quarter of 2019 and zero otherwise. Heteroskedasticity-robust standard errors clustered by bank are reported in parentheses.

	(1)	(2)	(3)	(4)
Year 2020 x IT index	0.0099***	0.0096***	0.0181***	0.0189***
	(0.0027)	(0.0029)	(0.0028)	(0.0031)
Q4 2019 x IT index		-0.0009		0.0033
		(0.0040)		(0.0035)
ln(Total assets)			-0.4528***	-0.4530***
			(0.0266)	(0.0265)
Equity/Assets			0.0131***	0.0131***
			(0.0019)	(0.0019)
Tier 1 ratio			-0.0050***	-0.0050***
			(0.0012)	(0.0012)
RoA			0.0013	0.0012
			(0.0034)	(0.0034)
Cost/Income			-0.0001	-0.0002
			(0.0003)	(0.0003)
Funding cost			0.0195***	0.0195***
			(0.0046)	(0.0046)
Personnel costs			0.0003	0.0003
			(0.0005)	(0.0005)
Bank FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
N	15,297	15,297	14,466	14,466
R^2	0.372	0.372	0.476	0.476

A Internet appendix

A.1 IV analysis - first stage results

Table A.1
Bank IT Strength and PPP Lending During the Pandemic (IV)– first stage

This table shows the first stage results of an instrumental variable analysis using three different instruments. The dependent varible is shown above each column. *Non-bank IT (dep.-w.)* is the average non-bank establishment level IT index in the zip codes covered by the bank's branch network, weighted by deposits. *Non-bank IT (HQ)* is the average non-bank IT index at the bank's headquarter zip code. *N internet providers* is the deposit-weighted number of internet providers a decade ago across the bank's branch network. Heteroskedasticity-robust standard errors clustered by county and bank are reported in parentheses.

	(1)	(2)	(3)
Non-bank IT (dep.-weighted)	0.1321***		
	(0.0339)		
Non-bank IT (bank HQ)		0.0973***	
		(0.0218)	
N internet providers			0.0074***
			(0.0025)
ln(Total assets)	0.1366***	0.1368***	0.1442***
	(0.0079)	(0.0078)	(0.0081)
Equity/Assets	0.0016	0.0005	0.0024
	(0.0039)	(0.0038)	(0.0041)
Tier 1 ratio	-0.0035*	-0.0034*	-0.0041**
	(0.0020)	(0.0019)	(0.0021)
RoA	0.0784***	0.0845***	0.0864***
	(0.0255)	(0.0245)	(0.0274)
Cost/Income	0.0066***	0.0068***	0.0076***
	(0.0013)	(0.0013)	(0.0013)
Funding cost	-0.0735***	-0.0660***	-0.0821***
	(0.0241)	(0.0237)	(0.0256)
Personnel costs	-0.0031**	-0.0031**	-0.0035**
	(0.0015)	(0.0015)	(0.0016)
N states	0.0039***	0.0040***	0.0031**
	(0.0012)	(0.0012)	(0.0012)
N	2,576	2,562	2,381
R^2	0.316	0.321	0.317

A.2 Alternative IT measures

Table A.2
Branch Visits During Mobility Restrictions vs. Bank IT (alternative)

	(1)	(2)	(3)	(4)
Restr.	-0.0272***	-0.0267***	-0.0116	-0.0175**
	(0.0068)	(0.0066)	(0.0080)	(0.0081)
Restr. x IT staff	-0.3147***			
	(0.0462)			
Restr. x IT budget		-0.0408***		
		(0.0028)		
Restr. x IT index (other)			-0.0042***	-0.0026***
			(0.0004)	(0.0007)
Restr. x IT index				-0.0194***
				(0.0063)
Branch FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
N	377,851	386,076	220,825	220,825
R^2	0.8522	0.8519	0.8379	0.8379

Table A.3
Website Traffic vs. Bank IT (alternative)

	(1)	(2)	(3)	(4)
IT index (other) x Restr.	1.2734***	0.6931**		
	(0.1613)	(0.2920)		
IT index x Restr.		0.4857**		
		(0.2157)		
IT budget x Restr.			0.1848***	
			(0.0527)	
IT staff x Restr.				4.9249***
				(1.2741)
Restr.	-0.7414***	-0.7465***	-0.5046***	-0.5414***
	(0.1446)	(0.1451)	(0.1274)	(0.1303)
Bank FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
N	3,595	3,595	3,480	3,480
R^2	0.5828	0.5834	0.5800	0.5810

Table A.4
PPP Lending and Alternative Measures of IT

The dependent varible is *ln(PPP loans)*, the bank-county level amount of PPP loans originated. *ln(CRA loans)* is the natural logarithm of the total amount of CRA small business lending in 2018 by the same bank to the same county. Heteroskedasticity-robust standard errors clustered by county and bank are reported in parentheses.

	(1)	(2)	(3)	(4)
IT index (other)	0.3675***	0.0112		
	(0.1305)	(0.1574)		
IT index		0.5170***		
		(0.1415)		
IT staff			2.7778**	
			(1.1748)	
IT budget				0.3783***
				(0.0945)
ln(CRA loans)	0.4338***	0.4344***	0.4362***	0.4286***
	(0.0194)	(0.0189)	(0.0193)	(0.0181)
ln(Deposits)	0.4076***	0.4082***	0.4064***	0.4109***
	(0.0133)	(0.0131)	(0.0134)	(0.0127)
ln(Total assets)	-0.1351***	-0.1636***	-0.0880**	-0.0337
	(0.0485)	(0.0490)	(0.0420)	(0.0353)
Equity/Assets	0.0388*	0.0435**	0.0346*	0.0518**
	(0.0220)	(0.0210)	(0.0207)	(0.0216)
Tier 1 ratio	-0.0909***	-0.0822***	-0.0931***	-0.0918***
	(0.0213)	(0.0210)	(0.0215)	(0.0220)
RoA	-1.0304**	-1.0986**	-0.9823*	-0.6803
	(0.5236)	(0.5112)	(0.5407)	(0.4362)
Cost/Income	-0.0028	-0.0041	-0.0029	0.0006
	(0.0092)	(0.0090)	(0.0089)	(0.0085)
Funding cost	-0.6345	-0.6662	-0.5964	-1.4056**
	(0.7846)	(0.7372)	(0.7580)	(0.6371)
Personnel costs	-0.0099	-0.0083	-0.0111	-0.0103
	(0.0125)	(0.0122)	(0.0121)	(0.0124)
N states	-0.0090**	-0.0092**	-0.0083**	-0.0131***
	(0.0042)	(0.0040)	(0.0039)	(0.0035)
County FE	Yes	Yes	Yes	Yes
HQ State FE	Yes	Yes	Yes	Yes
N	27,873	27,873	27,873	27,873
R^2	0.681	0.682	0.681	0.683

Table A.5
Bank IT Strength and Deposit Growth During the Pandemic (alternative measures)

The dependent variable is Δ *ln(Deposits)*, the quarterly change in the natural logarithm of bank-level deposits. Heteroskedasticity-robust standard errors clustered by bank are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Year 2020 x IT index (other)	0.0156***	0.0150***	0.0061*	0.0042				
	(0.0027)	(0.0031)	(0.0032)	(0.0036)				
Q4 2019 x IT index (other)		-0.0027		-0.0078				
		(0.0039)		(0.0053)				
Year 2020 x IT index			0.0144***	0.0164***				
			(0.0033)	(0.0037)				
Q4 2019 x IT index				0.0079				
				(0.0049)				
Year 2020 x IT staff					0.0330*	0.0415**		
					(0.0186)	(0.0203)		
Q4 2019 x IT staff						0.0336		
						(0.0246)		
Year 2020 x IT budget							0.0074***	0.0074***
							(0.0019)	(0.0020)
Q4 2019 x IT budget								0.0001
								(0.0020)
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	14,466	14,466	14,466	14,466	14,466	14,466	14,466	14,466
R^2	0.476	0.476	0.476	0.477	0.474	0.474	0.475	0.475

A.3 Likelihood of Switching Banks

Table A.6
Likelihood of Switching Banks

The dependent variable is shown above each column. *Switch to higher* is a dummy taking the value one if the firm switched banks when obtaining PPP loan (obtained a PPP loan from a different bank than its earlier SBA loan), and the new bank has better IT than its earlier lender. *Switch to lower* is a dummy taking the value one if the firm switched banks when obtaining PPP loan (obtained a PPP loan from a different bank than its earlier SBA loan), and the new bank has worse IT than its earlier lender. In Panel A, this better/worse IT classification is based on *IT index*. In Panels B and C, we show the same analysis based on alternative IT measures. Heteroskedasticity-robust standard errors clustered by county and bank are reported in parentheses.

Panel A: Likelihood of switching (based on IT index)

	Switch to higher (IT index)			Switch to lower (IT index)		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(COVID)	3.7380***	2.3697**	7.5749**	-3.6834**	-1.3946	-5.1980*
	(1.4283)	(1.1694)	(3.7590)	(1.5418)	(1.6095)	(3.0843)
IT Index (SBA)	-2.2157***			4.6492***		
	(0.2778)			(1.0204)		
ln(COVID) x IT Index (SBA)			-0.7154			0.5228
			(0.4518)			(0.4260)
SBA Lender FE	No	Yes	Yes	No	Yes	Yes
NAICS3 FE	Yes	Yes	Yes	Yes	Yes	Yes
N	27,624	27,624	27,624	27,624	27,624	27,624
R^2	0.0493	0.2043	0.2046	0.1333	0.2671	0.2672

Panel B: Likelihood of switching to higher IT (alternative measures)

	Switch to higher			
	IT index	IT index (other)	IT budget	IT staff
	(1)	(2)	(3)	(4)
ln(COVID)	2.3697**	3.5579***	2.3938**	2.1765
	(1.0054)	(1.0847)	(1.1619)	(1.3950)
SBA Lender FE	Yes	Yes	Yes	Yes
NAICS3 FE	Yes	Yes	Yes	Yes
N	27,624	27,624	25,304	17,149
R^2	0.2043	0.2267	0.2446	0.2459

Panel C: Likelihood of switching to lower IT (alternative measures)

	Switch to lower			
	IT index	IT index (other)	IT budget	IT staff
	(1)	(2)	(3)	(4)
ln(COVID)	-1.3946	-2.6512*	-1.7797	-1.1354
	(1.6095)	(1.5336)	(1.5003)	(1.6242)
SBA Lender FE	Yes	Yes	Yes	Yes
NAICS3 FE	Yes	Yes	Yes	Yes
N	27,624	27,624	25,304	17,149
R^2	0.2671	0.2897	0.1346	0.1899

A.4 Additional IV analysis

Table A.7
Branch Visits During Mobility Restrictions vs. Bank IT (IV)

This table tests the impact of mobility restrictions on branch visits for banks during the COVID-19 pandemic. The unit of observation is a branch-week. The dependent variable, *ln(Branch visits)* is the number of visits recorded in Safegraph's Places of Interest file. We instrument *IT index* by three alternative instruments: *Non-bank IT (dep.-w.)*, the average non-bank IT index across establishments in the zip codes covered by the bank's branch network, weighted by deposits, *Non-bank IT (HQ)*, the average non-bank IT index at the bank's headquarter zip code, and *N internet providers*, the deposit-weighted number of internet providers in 2010 across the bank's branch network that year. *Restr.* is a dummy indicating that there are mobility restrictions in place in the country. The sample period is February 1, 2020 to April 30, 2020. Robust standard errors clustered by county are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
IT index	-0.0429***	-0.0235***	-0.0313***	-0.0122*	-0.0310***	-0.0088*
	(0.0056)	(0.0051)	(0.0056)	(0.0062)	(0.0047)	(0.0048)
Restr.	-0.3649***		-0.0041		-0.0041	
	(0.0133)		(0.0100)		(0.0097)	
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
CountYes-Date FE	No	Yes	No	Yes	No	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
IV	N internet p.	N internet p.	Non-bank IT (HQ)	Non-bank IT (HQ)	Non-bank IT (dw.)	Non-bank IT (dw.)
F-statistic	22.62	15.29	6.26	3.79	134.04	81.95
N	381,543	381,543	385,512	385,512	386,236	386,236
R^2	0.8443	0.8667	0.8514	0.8671	0.8515	0.8672

Table A.8
Bank IT Strength and Deposit Growth During the Pandemic (IV)

The dependent variable is Δ *ln(Deposits)*, the quarterly change in the natural logarithm of bank-level deposits. Heteroskedasticity-robust standard errors clustered by bank are reported in parentheses.

	Non-bank IT (dep.-w.)		Non-bank IT (HQ)		N internet providers	
	(1)	(2)	(3)	(4)	(5)	(6)
Year 2020 x IT index	0.0580***	0.0576***	0.0428***	0.0427***	0.0562***	0.0592***
	(0.0120)	(0.0128)	(0.0108)	(0.0115)	(0.0165)	(0.0179)
Q4 2019 x IT index		-0.0014		-0.0004		0.0115
		(0.0136)		(0.0126)		(0.0218)
ln(Total assets)	-0.4592***	-0.4591***	-0.4573***	-0.4572***	-0.4574***	-0.4582***
	(0.0265)	(0.0266)	(0.0265)	(0.0266)	(0.0280)	(0.0283)
Equity/Assets	0.0137***	0.0137***	0.0135***	0.0135***	0.0137***	0.0137***
	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0020)	(0.0020)
Tier 1 ratio	-0.0051***	-0.0051***	-0.0051***	-0.0051***	-0.0047***	-0.0047***
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0013)	(0.0013)
RoA	0.0022	0.0022	0.0020	0.0020	0.0005	0.0005
	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0036)	(0.0036)
Cost/Income	-0.0002	-0.0002	-0.0001	-0.0001	-0.0003	-0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Funding cost	0.0210***	0.0210***	0.0203***	0.0203***	0.0176***	0.0176***
	(0.0047)	(0.0047)	(0.0047)	(0.0047)	(0.0049)	(0.0049)
Personnel costs	0.0003	0.0003	0.0003	0.0003	0.0004	0.0004
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0006)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	14,460	14,460	14,382	14,382	13,377	13,377
R^2	0.182	0.182	0.193	0.193	0.184	0.184

A.5 Bank share price performance

Figure A.1: Share Price Development vs. IT Index

Equally weighted stock price index of banks with high vs. low IT index.