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

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Abstract

Banks' IT capabilities affect 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. Stronger-IT banks are able to originate more PPP loans to small business borrowers, especially in areas with more severe COVID-19 outbreaks, higher internet use, and higher bank competition. Those banks also attract more deposit flows. Our findings are robust to using instrumental variables that capture exogenous variation in bank IT.

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 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). While 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 the ability to address under-served clienteles (e.g., Tang, 2019), recent evidence suggests brick-and-mortar banking still seems to matter a great deal.[2]

One challenge to studying the role of IT in the traditional banking sector is that both consumer preferences for technology and bank technology itself evolve over long periods of time, possibly endogenously to one another. In this paper, we study how banks' IT capabilities affect their ability to serve retail customers in response to an exogenous demand shock for digital banking services. The COVID-19 pandemic represents a unique natural experiment for our study, as large-scale mobility restrictions imposed by state and local governments in response to public health risks have led to substantial barriers to physical banking. Anecdotal evidence suggests that the use of digital banking has substantially increased during the pandemic.[3] 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

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

[2] Branch closings can lead to persistent declines in small business lending (Nguyen, 2019) and less competitive loan markets (Bonfim, Nogueira, and Ongena, 2020). Herpfer, Mjøs, and Schmidt (2021) find evidence that reductions in travel time lower banks' transaction costs and facilitate banking relationships.

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

mid-March 2020.[4] 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 banking.[5] At the same time, the pandemic has forced operational changes as back office personnel's ability to be in the office has also been restricted.

This unexpected and unprecedented demand shock for digital banking services provides us with an opportunity to study the role of banks' digital capabilities in affecting how they serve retail customers.[6] Utilizing a variety of data sources, we examine a number of outcomes, including physical branch visits, website traffic, SBA Paycheck Protection Program (PPP) lending to small businesses, customers' propensity to switch banks, and deposit flows. Across these various outcomes, we find that better IT explains a more pronounced shift away from in-person banking toward online banking and better ability to provide service to retail customers. We also investigate various mechanisms for this set of findings.

Our study uses an *IT index* measuring the presence of technologies that we deem likely to be useful for virtual, automated, or remote work. To construct this IT index, we use data from Aberdeen Computer Intelligence Database, which tracks the usage of technologies at the establishment level. Of the 63 key technology areas tracked by Aberdeen, we identify 14 technologies that, ex ante, seem relevant for facilitating a shift from physical to digital operations. This shift might entail staff working from home, bank personnel serving customers via website, phone or video chat, or increasing automation of previously manual processes. Thus, the IT index includes technologies such as VPN and remote access, document management, collaborative software, customer relationship management software, video conference and internet phone software, database software and server virtualization. We define *IT index* as the sum of 14 dummies, indicating the presence of each of the relevant technologies, and

[4] *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/

[5] 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/).

[6] While banks may adjust their IT in response to the pandemic, in the short-term, we expect there to be considerable variation in the extent of pre-existing IT investment by banks.

aggregate it to the bank level.[7] While this is our preferred measure, our findings are robust to other measures of IT as well.[8]

Armed with this measure, we begin by studying bank IT and the shift of bank customers from physical branches to online. First, we study physical visits to bank branches. Our measure of visits to physical bank branches come from SafeGraph, whose anonymized and aggregated data cover 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 after - but not before - the imposition of 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 decrease by 13% of their within-branch standard deviation.

We then perform a complementary analysis on traffic to banks' websites. We use data on the AlexaRank top one million websites. This allows us to measure the relative rankings of visitor volumes on bank websites over time. While we do not see the actual volume that the ranking is based on, the data allow cross-sectional comparisons of changes in website volumes on a weekly basis. Better IT is associated with a significantly larger increase in website traffic rank due to mobility restrictions. The economic magnitude is large: a one-standard-deviation increase in IT increases the shift from mobility restrictions by 7%.

A related finding is that a higher-IT index is associated with observable differences in banks' websites. Using data from BuiltWith, we calculate the number of "web technologies" present on banks' websites.[9] While not all technologies are equally important, more tech-

[7]The reasons for using a bank-level index are to reduce noise in the data and to reflect the fact that much of the digital infrastructure is not likely to be office specific.

[8]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. These additional analyses show that our findings are not sensitive to the definition of the IT measure.

[9]A web technology can comprise many types, including graphical technologies such as jQuery, web traffic

nologies likely implies greater technological investment and sophistication. Our IT index is significantly positively correlated with website technologies. In addition, in response to the pandemic, BuiltWith data began identifying the first time that the bank website mentions the COVID-19 pandemic. We find that a one-standard-deviation increase in IT index is associated with 1-4 days reduction in reaction time, depending on model specification. This suggests banks with better IT have more sophisticated web servers and adapted faster to the pandemic.

One potential concern with the above analysis is that banks are different along other dimensions correlated with IT. To further mitigate such concerns, we perform an instrumental variables analysis using two different instruments for bank IT. First, we calculate the weighted average number of internet providers across the bank branch network in the year 2010, a decade before the pandemic. This instrument captures differences in incentives to invest in IT that are not related to its business model or customers. Second, we calculate the number of cyber attacks between 2010 and 2015 to (other) entities around the bank's physical footprint. As such events are likely to make cyber risks more salient, they can give banks greater incentives to improve their IT before the pandemic. Both instruments capture aspects of the bank's IT quality that are not directly related to its current business but rather dictated by the historical shocks across the locations where it operates. Our results are robust to using either of these two instruments. Taken together, these results suggest better bank IT significantly leads to greater substitution from offline to online activity due to mobility restrictions.

That better IT facilitates banking customers toward digital services is important unto itself for public health reasons. Moreover, it can also have real economic consequences. Next, we focus on banks' ability to serve small and medium enterprise (SME) borrowers by investigating loans originated under the SBA Paycheck Protection Program (PPP).[10]

services such as content-delivery networks or the type of web server, security certificates, and much more.

[10]The PPP programme is the US government's SME support program, structured as government-guaranteed loans distributed through the banking system.

We consider the PPP lending to be a good setting to test the role of IT on banks' retail business, since PPP loans are an unexpected new loan product that banks had to set up under substantial time pressure and during a period when staff were potentially unable to physically be in the office. These significant operational frictions may have impacted banking relationships: prior evidence shows that bank relationships remain important for obtaining PPP loans (e.g., Li and Strahan, 2020), as the pool of PPP funds was limited, and as banks prioritized larger borrowers, possibly at the expense of SMEs (e.g., Balyuk, Prabhala, and Puri, 2020). Correspondingly, media articles suggest that many SME customers experienced poor service from their traditional banks and, at least in some cases, switched 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...".[11]

We perform two analyses to test the hypothesis that bank IT leads to better performance in distributing PPP loans. On the extensive margin, we perform a bank-county-level analysis to examine how the amount of PPP loan origination varies by the bank's IT capability. On the intensive margin, we study how IT affects which bank is chosen by a small business borrower. Turning to our first analysis, we find that, within the same county, banks with better IT originate significantly larger amounts of PPP loans during the pandemic, controlling for bank characteristics as well as the bank's prior activities in the county. 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. It is worth noting that these results are found when including county fixed effects, controlling for any unobserved factors that might affect local small business credit demand and quality, as well bank headquarter fixed effects.

We also investigate the differential relation between IT and PPP performance across

[11] *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

counties with different characteristics. First, if our results are driven by the ability of banks with good-IT to better serve customers with digital banking demand 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. The evidence confirms this prediction. 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. We find that the effect of IT is larger in areas with greater bank competition, as measured by a lower Herfindahl–Hirschman Index (HHI) of SME loans. This suggests that a stronger IT capability can be particularly valuable to banks operating in a competitive market.

We now turn to our second PPP analysis on the intensive margin. If IT is a determinant of a bank's ability to help small businesses obtain PPP loans, we might expect firms with existing relationships with low-IT banks to be more likely to switch to higher-IT banks for PPP loans when they are exposed to the COVID-19. To test these predictions, we form a sample of PPP borrowers who were also regular SBA-loan borrowers prior to the pandemic.[12] We find that 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. This suggests that customers prefer higher-IT banks over their previous banking relationship when COVID-19 cases - a proxy for the size of the demand shock - are greater.

A natural extension of the idea that high-IT banks gain customers during the pandemic is that such banks may also attract more deposit flows. Hence, we study the relationship between bank IT and deposit growth during the onset of the COVID-19 pandemic. Levine, Lin, Tai, and Xie (2021) 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. This suggests

[12] We caution that the PPP only names borrowers of a threshold size while SBA borrowers, by definition, are also small businesses. Still, we obtain sample of over 32,000 borrowers present in both datasets.

that banks that are better able to serve customers during the pandemic also attract more deposits during the COVID-19 shock, consistent with customers switching their banking relationships.

Our results suggest banks with better IT capabilities ex ante exhibit better performance during the pandemic when demand for digital banking increases. We also examine two potential interpretations of these findings. First, the evidence might suggest that banks with better IT have a superior ability to operate and serve their customers during the pandemic. Alternatively, it could be that banks with better IT have more IT-savvy clienteles even before the pandemic. Thus, our results would reflect IT-savvy customers shifting their behavior to digital services during the pandemic rather than a supply side constraint. Both interpretations are interesting and may simultaneously be at play, but have different implications for policymakers. While we cannot rule out either interpretation conclusively, the evidence is not consistent with clientele-sorting. To investigate clientele effects, we examine the relationship between bank and customer firm IT before the pandemic and find no significant relationship between the two.[13] Also, as noted before, we find firms *switched* from lower-IT banks to higher-IT banks. Thus, our results are unlikely to be explained by sorting between tech-savvy clienteles and high-IT banks that existed prior to the pandemic. Rather, it is more likely that IT served as a source of banks' competitive advantage in serving and acquiring customers.

We make several important contributions. First, we provide novel evidence of the impact of technology on bank outcomes. Our focus on a setting with an unexpected demand shock for digital banking services and this empirical design mitigates the identification challenge that both (1) consumer preferences technology evolve over a long time period, and (2) bank performance may lead to longer term investments in IT. Here, we hold fixed IT and observe exogenous demand for digitally-administered financial services. Other contemporaneous studies of the role of IT and bank operations include Branzoli, Rainone, and Supino

[13]For IT budget and IT staff, there is a *negative* relationship between bank and customer IT, which is the opposite of what we might expect if there was ex-ante matching of banks and customers based on IT.

(2021) and Core and De Marco (2021), who focus on Italian data. Our focus is on the US, we measure IT more comprehensively, including technologies helpful to banks during the pandemic (as opposed to IT investments of other kind), and our of footfall and web traffic help to establish the mechanisms through which IT helps improve bank performance during the pandemic. Our results are also related to the study by Pierri and Timmer (2020), who 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 to 2009.

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 examine the technological readiness of banks by looking at the substitution between banks depending on their digital capabilities. Given that banks are heavily regulated and play roles that alternative finance lenders may not be allowed to replace, this may represent a fruitful direction for future research as well.

Third, we add to the literature on the economic effects of the COVID-19 pandemic. 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 fungibility between banks' online and offline services can reduce the economic impact of mobility restrictions. Our results have broader implications beyond banking to any business considering the costs and benefits of technology adoption versus expanding physical presence. Our findings highlight the importance of good-IT infrastructure in mitigating operational risks and increasing flexibility in unexpected situations.

2 Relevant literature

2.1 Banks, technology, and branches

A vast literature studies the implications of technological change on banking. 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 broadening the reach of banks. 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. Berger and DeYoung (2006) find that technological progress has facilitated banks' geographic expansion further away from parent banks. Daniel, Longbrake, and Murphy (1973) find evidence of the use of computers facilitating economies of scale. Historically, 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.

However, extant studies on the role of IT in bank productivity are somewhat mixed. Berger (2003) argues that technology in banking has led to improvements in cost efficiency and lending capacity, while 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. Moreover, evidence suggests 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 ascribe the observed price differences to transportation costs. Nguyen (2019) shows that branch closings lead to persistent declines in small business lending. Garmaise and Moskowitz (2006) study the consequences of bank presence and competition: 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.

Mixed evidence of IT on bank outcomes may reflect the endogeneity of how trends in bank performance affect banks choice of IT investments. Relative to this literature, our study reflects the first exogenous shock to demand for digital services, allowing us to isolate how IT affects variation in bank outcomes.

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 the potential competitive advantage that technology can provide. Berger and Black (2019) contends 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 (p2p) 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 faster and adjust supply more elastically than other lenders without incurring higher default costs. Beyond technology, Buchak, Matvos, Piskorski, and Seru (2018) also show 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 reach underserved clienteles, whether fintech firms and traditional financial institutions are complements or substitutes remains a debate. 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.

Our study is unique from the fintech literature in that we focus extensively on the technological capabilities of incumbent banks rather than the fintech firms that aim to displace them. As our study is brought about by the pandemic, we deliver insights on the ability of banks to substitute online and offline activity and to operate digitally. Our results suggest less that substantial variation in IT readiness remains.

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, 2020; 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. In 2019, the database covered roughly 3.2 million establishments in the United States, including about 85% of all establishments with employment headcount 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. Out of these technologies, we manually identify 14 that we consider likely to be 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 sum of 14 dummies indicating the presence of each of the technologies. We interpret the presence of these technologies as the bank having that technology capability and the absence thereof as an absence of that capability. We aggregate the index to a bank-level measure by employee-weighting our office-level IT measure.

While we think our choice of technologies relevant to remote work is reasonable, one might be concerned about the possibility of cherry-picking. To mitigate such concerns, we show in the Internet Appendix that our analysis is robust to using alternative IT measures. First, we construct *IT index (other)*, calculated analogously to our main index, but including only the technologies excluded from the main measure. Examples of the remainder of the 63 categories include technologies such as workstations, phone provider, internet providers and generic business categories. This allows us to also test whether remote IT technologies (*IT index*) are generally more strongly linked to economic outcomes than *IT index (other)*. 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 not fully precise, 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 believe our simple count-based measures are preferable because they allow us to isolate technology investments that are particularly useful for remote work. Moreover, we argue that the breadth of capabilities should be more relevant than the amount spent for adapting business processes in a remote context. For example, a very expensive VPN is less useful than a suite of software services such as VPN, internet phones and video conferencing software.

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 the monthly number of visits at points-of-interest identified by SafeGraph, 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 data yields a sample of 32,146 branches for which we can study IT and footfall. We then construct a weekly panel dataset of physical branch visits at the branch level.

SafeGraph observes 18.75 million devices, approximately 5.6% of the U.S. population and about 10% of mobile devices. According to its analysis of user characteristics, SafeGraph posits that its sample is representative of the U.S. population based on income characteristics, age, and demographics of its users. The data are widely used in studies of social distancing during the COVID-19 pandemic (see, e.g., Charoenwong, Kwan, and Pursiainen, 2020; Weill, Stigler, Deschenes, and Springborn, 2020).

3.3 Measuring online traffic to banks

To measure online traffic on bank websites, we obtain data from Censys, a cybersecurity firm that monitors the AlexaRank top 1 million websites. Each observation is a company-week in which Censys gathered data about a particular website. We have 451 websites in the AlexaRank top 1 million in our sample for at least different 5 weeks from January to April 2020. For each observation from Censys, we have the AlexaRank, which captures the relative rankings of banks' websites at each point in time, which means that we cannot observe the actual underlying website traffic volumes, but we can observe changes in relative rankings and hence infer the relative changes in volumes. Based on these rankings, we define a variable *Online Traffic* which is defined as $log(10^6 - AlexaRank)$, so that higher values imply higher web traffic volumes.

3.4 Bank website composition and reaction times

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.

3.5 Small business lending

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. It 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 the total 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 also obtain the ex-ante SME lending volume measured as the total CRA small business lending by the same bank to the same county in 2018.[14]

3.6 Bank controls

Across different analyses, we measure bank financial characteristics using FDIC 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 equity and cost/income ratio), funding cost, personnel costs, and the number of states where the bank operates. At the timing of writing, we had data available through the second quarter of 2020.

3.7 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,

[14]This is the latest year of which the CRA data is available at the time of our analysis.

and other restrictions. To obtain an aggregate measure of the level of restrictions in place at each location, we calculate an index variable *Num. Restr.* 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).

3.8 Instrumental variables analysis

One possible concern with our study is that bank IT might be endogenous to other bank characteristics. For example, for our PPP analysis, one might wonder whether 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; ii) our analysis is designed in a manner that attempts to account for these challenges to identification.[15]

To further mitigate such concerns, we perform an instrumental variables analysis using two different instruments for bank IT, including i) the weighted-average number of internet providers in 2010 across the bank's branch network and ii) the number of cyber attacks that organizations around the bank's physical presence are exposed to. The idea with the first is that banks in areas with better network infrastructure early on may have more incentives to invest in IT infrastructure, independent of the bank's business model and customer base. With the second instrument, cyber attacks around bank locations are likely to make IT infrastructure issues more salient to the bank's management and hence spur investment in IT capability. The exclusion restriction in our case means that the instruments should not affect bank activities through channels other than IT. The vast majority of cyberattacks in our sample target medical establishments, and hence are plausibly disconnected from IT problems at the bank.

[15] At least for our outcome SME lending outcome variable, our comparison across lending by different banks within the same county, such that all observed and unobserved economic fundamentals that influence local credit demand is pinned down. Moreover, 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 measure the number of internet providers, we use data from the Federal Communications Commission for each zip code of banks' branches and calculate a deposit-weighted average for each bank. To measure banks' exposure to cyber attacks, we use data from Privacy Rights Clearinghouse. We first count in each zip code the number of data breach incidents (experienced by any organization, not only banks) during 2010 to 2015. Then for each bank, we compute the average number of data breaches across zip codes where the bank has branches, weighted by the bank's deposits in each corresponding zip code. The natural logarithm of this weighted average data breach count is then used as an instrumental variable in our analysis.

While our IV analysis will conform to the unit of observation in each of our analyses, we conduct a bank-level first-stage regression analysis. The results are reported in Table A.1 in the Internet Appendix. They show that, controlling for other bank characteristics, both instruments strongly explain the cross-bank variation of IT. In particular, banks more exposed to cyber attacks and whose branches are exposed to better internet have better IT index values.

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 to bank branches for banks with high, medium and low IT index values over time. Our sample period is February 1 to April 30, focusing on a narrow window before and after the onset of the pandemic in the United States.[16] Following the introduction of mobility restrictions, there is a clear divergence between high-IT and low-IT banks, with branch visits decreasing

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

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:

$$ln(Branch\ visits)_{i,t} = \alpha_i + \beta NumRestr._{c,t} \times IT\ index_j + \gamma NumRestr._{c,t} + \phi X_{i,t} + \epsilon_{i,t} \quad (1)$$

where *Branch visits* is the weekly number of visits at branch i. *Num Restr.* is a count of restrictions which tally the number of mobility restrictions 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 week fixed effects and state-week 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 7% larger reduction in branch visits relative to the residual standard deviation (coefficient of -0.0042 x standard deviation of 6.23 of ($ITIndexxNumRestr.$) / 0.376 7.1%) conditional on mobility restrictions. 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 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. Column 2 is consistent with this prediction prediction. Column 3 re-runs Column 1 with county-week fixed effects, which show that *within-county* that the banks with better IT see a bigger drop in footfall than those banks with weaker IT.

Columns 4 and 5 conduct our instrumental variable analyses on the interaction of IT with the number of restrictions. Both of our instrumental variables register significant first stage F-statistics (21.52 and 98.76 respectively). The corresponding second stage coefficients register with F-statistics above 5 and our coefficients are similar in size to our reduced form estimates.

4.2 Website traffic and COVID-19

We next perform an complementary analysis comprised of studying the visits to the bank's website. We use Censys data on the website traffic volumes of the AlexaRank top one million websites. This allows us to measure the relative rankings of visitor volumes on bank websites over time. While we do not see the actual volume that the ranking is based on, the data allow cross-sectional comparisons of changes in website volumes over time. AlexaRank does not include daily counts of web traffic for firms falling below a threshold, even if the website is in the AlexaRank top 1 million.. We have 451 websites in the AlexaRank top 1 million in our sample for at least different 5 weeks from January to April 2020. Any lapse in coverage not a problem for our analysis as long as mobility restrictions are not correlated with coverage by Censys' automated processes in AlexaRank. We believe that it is implausible for mobility restrictions and AlexaRank to be correlated. For mobility restrictions, we again use the number of restrictions. As a bank may have multiple establishments in multiple counties, we aggregate to the website level weighting each establishment based on the employment numbers Aberdeen reports for its locations.

The results, shown in Table 3, mirror those on branch visits. After mobility restrictions come into place, banks with better IT exhibit significantly larger increases in website traffic relative to banks with weaker IT. This suggests that when the demand for online services increases, banks with high quality IT gain on a relative basis. Column 1 reveals that a standard deviation movement in IT index increases the economic magnitude of mobility restrictions of roughly 12.7% of a residual standard deviation (0.067 x 4.032/2.12). Column 2 tests the parallel trends assumption, again finding evidence of an improvement that coincides with the onset of restrictions, but not before. Columns 3 and 4 repeat our instrumental variables exercises. In this sample, our instrumental variable again register significant first stage F-statistics.

To rationalize the above findings, we next check whether our IT index is correlated with characteristics of bank websites, which likely played a large role in digital provision of financial services. 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 implies greater technological investment and sophistication, and thus should be characteristic of banks with better IT.

In Columns 1 and 2 of Table 4, we perform a cross-sectional regression analysis of the number of website technologies conditional on the bank's IT index. Our 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.

Interestingly, one technology BuiltWith tracks is when websites mention the COVID-19 pandemic. We define a response time variable as the number of days between the first US COVID-19 case and the first time the bank website mentions the pandemic. Columns 3 and 4 of Table 4 show the results of a regression analysis of the response time to COVID-19 as implied by bank websites. 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. This suggests that firms which have better IT are able to respond more quickly to the pandemic.

4.3 Bank IT and PPP lending

4.3.1 PPP loan volumes

Next, we focus on the amount of small business loans originated under the SBA Paycheck Protection Program (PPP). This can be viewed as the extensive margin of PPP lending - we later examine the intensive margin in 4.3.3. 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:

$$PPP_{i,c} = \alpha_c + \gamma_{hq} + \beta IT\ index_i + \phi X_{i,c} + \delta X_i + \epsilon_{i,c} \tag{2}$$

where $PPP_{i,c}$ is the natural logarithm of the volume of PPP loans originated by bank i in county c. $X_{i,c}$ is a vector of pre-pandemic bank-county level controls, including the log amount of CRA small business lending by the same bank in the same county and the log level of deposits to branches of the same banks in the same county before the pandemic. X_i is a vector of bank characteristics, including bank size (measured by total assets), capitalisation (measured by both equity/asset ratio and tier 1 capital ratio), profitability (measured by return on equity 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 γ_{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 Panel A of 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 to controlling for the ex-ante SME lending as well as deposits of the same bank to the same county. It is also robust to controlling for county fixed effects (which pin down all unobserved variations in local credit demand and quality) as well as 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.

Columns 5 and 6 of Table 5 report the second stage IV regression results. Column 5 uses the weighted-average number of internet providers in 2010 across the bank's branch network to capture the exogeneous variations of bank IT capacity, while Column 6 uses the number of cyber attacks that organizations around the bank's physical presence are exposed to. The positive effect of bank IT on PPP lending to SMEs during the pandemic remains robust when estimated based on the more exogenous variation in bank IT as captured by each of these two instruments.

4.3.2 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 B of Table 5. According to the estimates in Column 1, if the number of confirmed COVID-19 cases doubles, the estimated effect of bank IT is about 20% higher compared to the average effect.

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 B of Table 5, 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. columns 5 and 6 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.

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.

4.3.3 Likelihood of switching banks

If weak IT results in poor service to customers during the pandemic, we might expect customers to switch to banks with better IT. This can be viewed as the intensive margin of PPP lending. Furthermore, we might expect such bank switching to be related to both the IT capability of the existing bank as well as to the severity of the COVID-19 impact at the location of the customer. We can empirically test these predictions for SME customers that are present in both SBA 7a programs and the PPP program. We match borrowers across these two datasets and form a panel of 33,424 firms that are borrowers in both whose borrowing occurred between 2017 and 2019.[17]

We define an outcome variable identifying bank switches conditional on the change in the bank IT index. This outcome variable is a dummy taking the value one if the firm changes

[17] The PPP only names borrowers with borrowing amounts above $150,000, while normal SBA loans target relatively smaller borrowers. Thus, the intersection of the two sets of firms a fraction of the total.

lenders to a bank with a higher-IT index than its pre-COVID lender had. Our hypothesis is that a firm facing more COVID-19 exposure should be more likely to switch to a lender that has a higher-IT score than their pre-COVID lender.

Our results are shown in Table 6. Consistent with the prediction, we find that a borrower is more likely to switch to a bank with better IT if it is in a county more affected by the pandemic. Column 2 shows that a higher pre-existing level of IT is negatively related to the probability of a bank switch toward a bank with higher-IT. Importantly, Column 3 shows that the effect of prior bank IT is larger in areas more severely affected by COVID-19. Taken together, the results suggest that a stronger demand shock (e.g. more COVID-19 cases) leads to a greater probability of switching to a bank with better IT.

4.4 Bank IT and deposit growth

We also look into the dynamic growth of bank deposits over the first two quarters of 2020 as another measure of 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:

$$\begin{aligned} \Delta ln(Deposits)_{i,t} =& \alpha_i + \gamma_t + \beta IT\ index_i \times Year\ 2020 + \\ & \theta IT\ index_i \times Q4\ 2019 + \phi X_{i,t-1} + \epsilon_{i,t} \end{aligned} \tag{3}$$

where $\Delta ln(Deposits)$ is the change in the deposits of bank i in a logarithmic form, measuring a relative change. α_i and γ_t are bank and quarter fixed effects. *Year 2020* is a dummy variable that equals one for the first two quarters in 2020 (where the pandemic is going on) and 0 otherwise. *Q4 2019* is a dummy variable that equals 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 equity and cost/income ratio), funding cost, and personnel costs.

The results are shown in Table 7. Better bank IT is associated with significantly higher deposit growth during the onset of the pandemic, and this effect is robust to controlling for other bank characteristics as well as the pre-pandemic trend. During the first two quarters of 2020, a one-standard-deviation higher bank IT can generate about 0.7% higher deposit flows, which is about 24% of the average deposit growth during the sample period. Moreover, banks with stronger IT also see a higher deposit sensitivity to COVID across the bank market network. Also, we confirm that our results are robust under the instrumental variable analyses.

5 Additional analysis and robustness checks

5.1 Discussion of alternative interpretations

In totality, our results suggest banks with better IT capabilities before the pandemic had better performance. Lastly, we examine the two potential interpretations of these findings. First, the evidence might suggest that banks with better IT had superior ability to operate during the pandemic. Alternatively, good-IT banks drew in IT-savvy clienteles prior to the pandemic. The IT-savvy customers shifted their behavior digitally in response to the pandemic. Both are interesting, but the first interpretation suggests that it is important for policymakers to focus on bank capabilities while the second suggests that the effect of IT operates through consumer preferences. In our view, the evidence is likely consistent with the first and not the second channel, although we cannot rule out either conclusively.

To help distinguish these views, we test whether we see clients with better IT prefer banks with better IT. To test this, we use the Small Business Administration (SBA) loan data to identify pre-pandemic lending relationships. We calculate the same IT measures as we use for banks for the SME borrowers in the SBA data and perform a regression analysis of the relationship between bank and firm IT.

The results are shown in Table 8. We report four specifications varying in the fixed effects accounting for the location and industry of the borrowing firm. We do not find a positive relationship between customer IT and bank IT in any of our regressions. In fact, the relationship is marginally negative, but insignificant. This suggests it is unlikely that high-IT banks' customers would be more likely to adopt digital banking services than other banks' customers prior to the pandemic. Hence, our findings regarding PPP are not likely driven by different clienteles' familiarity with digital technology. Our previous analysis on customers switching to better IT banks can also be seen as evidence that that IT-savvy customers did not sort with IT-savvy banks before the pandemic.

Also, as noted before, we find that firms *switched* from lower-IT banks to higher-IT banks, suggesting that existing clienteles of good-IT banks did not drive our findings entirely. Thus, while Covid-19 possibly spurred consumers to develop preferences for banking technology, the bank outcomes we observed are likely not solely explained by sorting between tech-savvy clienteles and high-IT banks that existed prior to the pandemic. Rather, it seems like IT served as a source of competitive advantage.

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. 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 a 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 a 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 a characteristic would also have to be correlated with local internet infrastructure and the number of cyber attacks.

5.2 Alternative IT measures

Next, we study whether our results are sensitive to the way we defined our IT index. In Internet Appendix Section A.2, we present our main analyses employing 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 analyses, 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.

6 Conclusion

We find that banks' IT capabilities affect their ability to serve customers during the demand shock for digital banking services generated by the COVID-19 pandemic. Better bank IT is associated with both a larger shift from offline to online as well as better ability to serve retail customers. In the areas harder hit by the pandemic, customers are more likely to switch to banks with better IT. While the COVID-19 outbreak represents an unprecedented 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 Covid-19 decreases. 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.

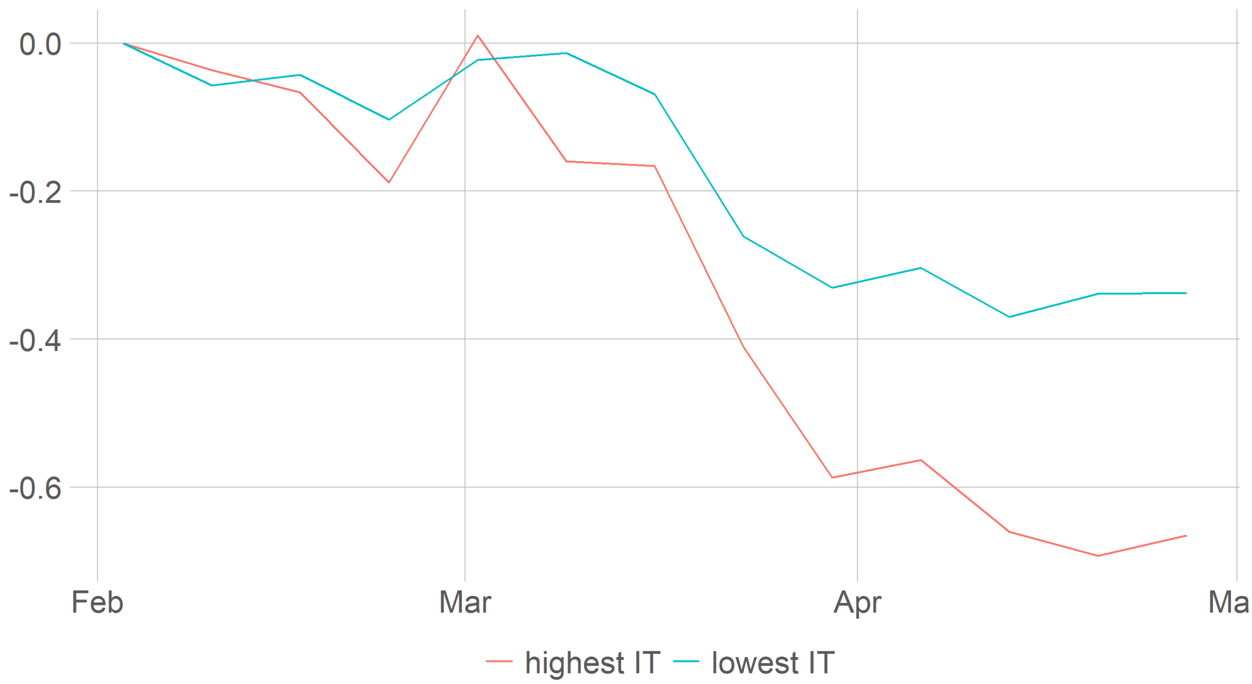

Table 1
Summary Statistics

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

	N	Mean	Std	p25	p50	p75
Bank level						
IT index	3,198	2.418	1.946	1.000	2.000	3.000
IT index (other)	3,163	8.998	5.074	6.000	8.000	10.264
ln(IT budget)	3,185	12.399	0.716	12.019	12.355	12.751
IT staff	3,187	0.137	0.070	0.089	0.133	0.178
Bank-Quarter level						
Δ ln(Deposits)	28,328	0.029	0.080	-0.007	0.018	0.052
ln(Total assets)	28,329	12.647	1.457	11.691	12.455	13.344
Equity/Assets	28,329	12.139	5.197	9.816	11.196	13.088
Tier 1 ratio	25,098	18.182	17.405	12.538	14.914	19.027
RoE	28,329	0.048	0.078	0.022	0.040	0.070
Cost/Income	28,320	68.916	23.501	58.617	67.294	76.475
Funding cost	28,329	0.462	0.356	0.207	0.354	0.625
Personnel costs	28,320	39.167	11.602	33.453	38.531	44.059
N states	28,329	1.315	1.509	1.000	1.000	1.000
Bank-Week level						
Online traffic	4,026	13.552	0.242	13.451	13.602	13.726
Branch-Week level						
Branch visits	392,897	14.841	33.903	3.000	8.000	18.000
Bank-County level						
PPP loans (USDm)	111,135	3.760	23.182	0.036	0.170	1.007
CRA loans (USDm)	191,235	1.266	10.366	0.000	0.011	0.250
Deposits (USDm)	191,235	67.000	2016.594	0.000	0.000	0.000

Table 2
Branch Visits During Mobility Restrictions

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. *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). *Num. Restr. (t+1)* assigns the same restriction number to the period before the actual restriction policy takes place. This variable captures the potential pre-trend. The sample period is February 1, 2020 to April 30, 2020. Columns (4) and (5) are instrumental variable analysis using two alternative instruments for IT index: *N internet providers*, the deposit-weighted number of internet providers in 2010 across the bank's branch network that year, and *N data breaches*, the average number of data breaches by (other) entities across the zipcodes where the bank is present. First-stage results are reported in the Internet Appendix. Heteroskedasticity-robust standard errors clustered by county and bank are reported in parentheses.

	OLS			IV-1	IV-2
	(1)	(2)	(3)	(4)	(5)
IT index x Num Restr.	-0.0042***	-0.0034***	-0.0011**	-0.0078***	-0.0043***
	(0.0006)	(0.0007)	(0.0005)	(0.0006)	(0.0008)
IT index x Num Restr. (t+1)		-0.0008			
		(0.0006)			
Num Restr.	-0.0076***	-0.0092***		-0.0062*	-0.0075***
	(0.0026)	(0.0022)		(0.0033)	(0.0026)
Num Restr. (t+1)		0.0021			
		(0.0024)			
Branch FE	Yes	Yes	Yes	Yes	Yes
County-Week FE	No	No	Yes	No	No
Week FE	Yes	Yes	No	Yes	Yes
F statistic (1st stage)				21.52	98.76
N	386,223	386,223	386,223	385,940	386,044
R^2	0.8657	0.8657	0.8796	0.8652	0.8657

Table 3
Website Traffic During Mobility Restrictions

This table tests 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 higher web traffic. AlexaRank is the website's weekly Alexarank recorded in Censys, a cybersecurity dataset. *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 restriction types in place). *Num. Restr. (t+1)* assigns the same restriction number to the period before the actual restriction policy takes place. This variable captures the potential pre-trend. The sample period is February 1, 2020 to April 30, 2020. Columns (3) and (4) are instrumental variable analyses using two alternative instruments for IT index: *N internet providers*, the deposit-weighted number of internet providers in 2010 across the bank's branch network that year, and *N data breaches*, the average number of data breaches of (other) entities across the zipcodes where the bank is present. Heteroskedasticity-robust standard errors clustered by bank are reported in parentheses.

	OLS		IV-1	IV-2
	(1)	(2)	(3)	(4)
IT index x Num Restr.	0.067***	0.068***	0.126***	0.141***
	(0.009)	(0.017)	(0.029)	(0.025)
IT index x Num Restr. (t+1)		-0.013		
		(0.015)		
Num Restr.	0.092	0.012	0.099	0.101
	(0.118)	(0.121)	(0.121)	(0.123)
Num Restr. (t+1)		0.192***		
		(0.070)		
Bank FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
F statistic (1st stage)			19.76	16.27
N	3,247	3,247	3,238	3,238
R^2	0.550	0.552	0.546	0.544

Table 4
Website Characteristics and COVID-19 Response Time

This table characterizes the relation between our measure of IT index 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. We control for bank characteristics including size (measured by total assets), capitalisation (measured by both equity/asset ratio and tier-1 capital ratio), profitability (measured by return on equity and cost/income ratio), funding cost, and personnel costs. Heteroskedasticity-robust standard errors clustered by bank are reported in parentheses.

	ln(1+Website Techs)		Response time	
	(1)	(2)	(3)	(4)
IT index	0.2333***	0.1598***	-1.9472***	-0.5299*
	(0.0079)	(0.0058)	(0.2304)	(0.2991)
Bank Controls	No	Yes	No	Yes
State FE	Yes	Yes	Yes	Yes
N	3,196	3,162	3,196	3,162
R^2	0.5073	0.5827	0.0679	0.1022

Table 5
PPP Lending During the Pandemic

This table estimates the effect of bank IT on PPP lending to small businesses. 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 pre-pandemic amount of CRA small business lending by the same bank to the same county. *ln(Deposits)* is the natural logarithm of pre-pandemic deposits to the same bank from the same county as reported in the SOD data. Columns (5) and (6) present the second stage results of an instrumental variable analysis using two alternative instruments for IT index: *N internet providers*, the deposit-weighted number of internet providers in 2010 across the bank's branch network that year (Column 5), and *N data breaches*, the average number of data breaches of (other) entities across the zipcodes where the bank is present (Column 6). In Panel B, *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 across banks in the county. We control for bank characteristics including size (measured by total assets), capitalisation (measured by both equity/asset ratio and tier-1 capital ratio), profitability (measured by return on equity and cost/income ratio), funding cost, personnel costs, and the number of states where the bank operates. Heteroskedasticity-robust standard errors clustered by county and bank are reported in parentheses.

Panel A: PPP Lending During the Pandemic and Bank IT

	OLS				IV-1	IV-2
	(1)	(2)	(3)	(4)	(5)	(6)
IT index	0.0910**	0.1311***	0.1040***	0.1059***	0.3484***	0.6543***
	(0.0390)	(0.0428)	(0.0324)	(0.0277)	(0.1282)	(0.2243)
ln(CRA loans)		0.5283***	0.4009***	0.4332***	0.4404***	0.4498***
		(0.0189)	(0.0262)	(0.0189)	(0.0196)	(0.0234)
ln(Deposits)		0.3944***	0.4292***	0.4090***	0.4094***	0.4092***
		(0.0133)	(0.0152)	(0.0130)	(0.0131)	(0.0141)
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	No	No	Yes	Yes	Yes	Yes
HQ State FE	No	No	No	Yes	Yes	Yes
N	28,145	28,145	27,873	27,873	27,765	27,769
R^2	0.047	0.584	0.661	0.682	0.560	0.499
F statistic (1st stage)					17.3	9.4

Panel B: Effects of COVID-19 cases, internet use, and local bank competition

	(1)	(2)	(3)	(4)	(5)	(6)
IT index x ln(COVID)	0.0216***	0.0137**				
	(0.0068)	(0.0067)				
IT index x Internet use			0.2110***	0.1534***		
			(0.0452)	(0.0423)		
IT index x HHI					-0.3280***	-0.2431***
					(0.0673)	(0.0619)
IT index	0.1040***		0.1057***		0.1000***	
	(0.0275)		(0.0267)		(0.0270)	
Bank controls	Yes	No	Yes	No	Yes	No
Bank-county controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
HQ State FE	Yes	No	Yes	No	Yes	No
Bank FE	No	Yes	No	Yes	No	Yes
N	27,873	27,869	25,540	25,537	27,873	27,869
R^2	0.682	0.717	0.680	0.715	0.682	0.717

Table 6
Likelihood of Customer Switching Banks for PPP Loan

This table estimates small businesses' likelihood of switching to stronger-IT banks during the pandemic. The dependent variable is *Switch bank*, 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 pre-COVID relationship banks from which it takes regular SBA loans), and the new bank has better IT than its earlier lender. This better/worse IT classification is based on *IT index*. Heteroskedasticity-robust standard errors clustered by county and bank are reported in parentheses.

	(1)	(2)	(3)
ln(COVID)	0.8846*	2.0160***	3.6118***
	(0.5061)	(0.3622)	(0.6773)
IT Index (pre-COVID bank)		-6.0306***	-4.6444***
		(0.4657)	(0.5089)
ln(COVID) x IT Index (pre-COVID bank)			-0.2177***
			(0.0691)
Industry (NAICS3) FE	Yes	Yes	Yes
N	33,250	33,250	33,250
R^2	0.0520	0.1856	0.1864

Table 7
Deposit Growth During the Pandemic

This table estimates the relation between bank IT and deposit flows during the pandemic. The dependent variable is Δ *ln(Deposits)*, the quarterly bank-level deposit growth. The sample period is 2019 Q1 to 2020 Q2. *Year 2020* is a dummy variable that equals one for the first two quarters of 2020 and zero otherwise. *Q4 2019* is a dummy variable that equals one for the last quarter of 2019 and zero otherwise. We control for bank characteristics including size (measured by total assets), capitalisation (measured by both equity/asset ratio and tier-1 capital ratio), profitability (measured by return on equity and cost/income ratio), funding cost, and personnel costs. Heteroskedasticity-robust standard errors clustered by bank are reported in parentheses.

	OLS			IV-1		IV-2	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Year 2020 x IT index	0.0034***	0.0033***		0.0196***		0.0074***	
	(0.0008)	(0.0009)		(0.0041)		(0.0022)	
Q4 2019 x IT index		-0.0001					
		(0.0008)					
ln(COVID) x IT index			0.0009***		0.0070***		0.0020**
			(0.0003)		(0.0015)		(0.0009)
ln(COVID)			0.0024**		-0.0010		0.0018
			(0.0010)		(0.0012)		(0.0011)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	26,769	26,769	26,769	26,559	26,559	26,671	26,671
R^2	0.448	0.448	0.448	0.197	0.189	0.217	0.217
F statistic (1st stage)				130.3	79.1	130.0	87.5

Table 8
Bank IT vs. Customer IT

This table shows the pre-pandemic relationship between bank and customer IT. The dependent variable is the *IT index* of the bank, and the independent variable is the *IT index* of the SME customer who had a borrowing relationship with the bank before the pandemic. Heteroskedasticity-robust standard errors clustered by firm county are reported in parentheses.

	(1)	(2)	(3)	(4)
IT Index (customer)	-0.0031	-0.0039	-0.0021	-0.0028
	(0.0029)	(0.0029)	(0.0024)	(0.0026)
Constant	1.6590***			
	(0.0243)			
County FE	No	Yes	No	Yes
Industry FE	No	No	Yes	Yes
N	38,949	38,949	38,949	38,949
R^2	0.00003	0.0650	0.1542	0.2087

A Internet appendix

A.1 IV analysis - first stage results

Table A.1
Bank IT, Internet Providers, and Data Breaches

This table shows the bank-level relationship between bank IT and the two different instrumental variables used in the IV analysis. The dependent varible is *IT index* of each sample bank before the pandemic. *N internet providers* is the deposit-weighted number of internet providers a decade ago across the bank's branch network. *N data breaches*, the average number of data breaches between 2010 and 2015 of (other) entities across the zipcodes where the bank is present. Heteroskedasticity-robust standard errors clustered by county and bank are reported in parentheses.

	(1)	(2)
N internet providers	0.0214***	
	(0.0056)	
N data breaches		0.0274***
		(0.0091)
ln(Total assets)	0.4195***	0.4217***
	(0.0200)	(0.0198)
Equity/Assets	-0.0053	-0.0047
	(0.0074)	(0.0072)
Tier 1 ratio	0.0103***	0.0104***
	(0.0022)	(0.0022)
RoE	0.3340	0.3367
	(0.3189)	(0.3220)
Cost/Income	0.0108***	0.0112***
	(0.0025)	(0.0026)
Funding cost	-0.0992	-0.0672
	(0.0648)	(0.0632)
Personnel costs	-0.0178***	-0.0180***
	(0.0040)	(0.0040)
N states	0.1257***	0.1160***
	(0.0170)	(0.0169)
N	4,770	4,790
R^2	0.290	0.290

A.2 Alternative IT measures

Table A.2
Branch Visits During Mobility Restrictions

This table repeats the analysis in Table 2 by using alternative measures for the IT capability of each bank. The alternative measures include a similar IT index measured based on other less relevant technologies, the number of bank IT staff (per employee), and the log amount of IT budget normalized by bank employee number. 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. Heteroskedasticity-robust standard errors clustered by county are reported in parentheses.

	(1)	(2)	(3)	(4)
Num Restr. x IT index (other)	-0.0011***	0.00004		
	(0.0001)	(0.0001)		
Num Restr. x IT index		-0.0130***		
		(0.0015)		
Num Restr. x IT staff			-0.1106***	
			(0.0168)	
Num Restr. x ln(IT budget)				−0.0146***
				(0.0010)
Branch	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
N	386,115	386,115	377,851	386,076
R^2	0.8517	0.8519	0.8522	0.8519

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

This table repeats the analysis in Table 3 by using alternative measures for the IT capability of each bank. The alternative measures include a similar IT index measured based on other less relevant technologies, the number of bank IT staff (per employee), and the log amount of IT budget normalized by bank employee number. The dependent variable is *Online Traffic* which is defined as $log(10^6 - Alexarank)$, scaled so higher values equal higher 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. Heteroskedasticity-robust standard errors clustered by bank are reported in parentheses.

	(1)	(2)	(3)	(4)
IT index (other) x Restr.	0.0805***	0.0463**		
	(0.0099)	(0.0181)		
IT index x Restr.		0.0937*		
		(0.0478)		
IT staff x Restr.			3.5311***	
			(1.2255)	
ln(IT budget) x Restr.				0.1110**
				(0.0457)
Restr.	-0.6129***	-0.6169***	-0.4372***	-0.4024***
	(0.1365)	(0.1371)	(0.1250)	(0.1208)
Bank FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
N	3,235	3,235	3,134	3,134
R^2	0.5493	0.5496	0.5465	0.5458

Table A.4
PPP Lending and Bank IT (alternative)

This table repeats the analysis in Table 5 by using alternative measures for the IT capability of each bank. The alternative measures include a similar IT index measured based on other less relevant technologies, the number of bank IT staff (per employee), and the log amount of IT budget normalized by bank employee number. 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. We control for bank characteristics including size (measured by total assets), capitalisation (measured by both equity/asset ratio and tier-1 capital ratio), profitability (measured by return on equity and cost/income ratio), funding cost, personnel costs, and the number of states where the bank operates. Heteroskedasticity-robust standard errors clustered by county and bank are reported in parentheses.

	(1)	(2)	(3)	(4)
IT index (other)	0.0200	-0.0325*		
	(0.0134)	(0.0174)		
IT index		0.1578***		
		(0.0368)		
IT staff			2.9414**	
			(1.1860)	
ln(IT budget)				0.3792***
				(0.0956)
ln(CRA loans)	0.4316***	0.4320***	0.4354***	0.4284***
	(0.0193)	(0.0184)	(0.0192)	(0.0183)
ln(Deposits)	0.4085***	0.4099***	0.4064***	0.4107***
	(0.0133)	(0.0130)	(0.0134)	(0.0128)
Bank controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
HQ State FE	Yes	Yes	Yes	Yes
N	27,873	27,873	27,873	27,873
R^2	0.680	0.682	0.681	0.683

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

This table repeats the analysis in Table 7 by using alternative measures for the IT capability of each bank. The alternative measures include a similar IT index measured based on other less relevant technologies, the number of bank IT staff (per employee), and the log amount of IT budget normalized by bank employee number. The dependent variable is Δ *ln(Deposits)*, the quarterly change in the natural logarithm of bank-level deposits. We control for bank characteristics including size (measured by total assets), capitalisation (measured by both equity/asset ratio and tier-1 capital ratio), profitability (measured by return on equity and cost/income ratio), funding cost, and personnel costs. Heteroskedasticity-robust standard errors clustered by bank are reported in parentheses.

	(1)	(2)	(3)	(4)
Year 2020 x IT index (other)	0.0013***	0.0003		
	(0.0004)	(0.0005)		
Year 2020 x IT index		0.0028***		
		(0.0011)		
Year 2020 x IT staff			0.0040	
			(0.0158)	
Year 2020 x ln(IT budget)				0.0047***
				(0.0013)
Bank controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
N	23,728	23,728	23,728	23,728
R^2	0.423	0.423	0.423	0.423