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# Stress Testing Banks' Digital Capabilities: Evidence from the COVID-19 Pandemic

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## Abstract

Banks' information technology (IT) capabilities affect their ability to serve customers during the COVID-19 pandemic, which generates an unexpected and unprecedented shock that shifts banking services from in-person to digital. 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 Paycheck Protection Program 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 and receive better mobile customer reviews during the pandemic.

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# I. 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 (IT) plays an important role in facilitating these changes, the evidence on the relationship between bank performance and IT investment is mixed (e.g., Berger (2003), Beccalli (2007), and 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 underserved clienteles (e.g., Tang (2019)), recent evidence suggests that brick-and-mortar banking still matters a great deal.[2]

One challenge to studying the role of IT in the traditional banking sector is that both bank IT investments and how they serve customers evolve over long periods of time, possibly endogenously to one another. In this article, we study how banks' IT capabilities affect their ability to serve retail customers in response to an exogenous shock that leads to a shift from physical branch banking to 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 Apr. 2020 relative to Apr. 2019 and a 23% surge in customers signing on to digital banking since mid-Mar. 2020 (*Wells Fargo Stories: Digital Banking Soars in the COVID-19 Pandemic*, available at https://stories.wf.com/digital-banking-soars-in-the-covid-19-pandemic/). Survey data suggest that banks have generally seen a double-digit rise in first-time online accounts, mobile deposits and payments, and overall usage of web and mobile banking.[4] At the same time, the pandemic has forced operational changes such as moving employees into remote work and branches into temporary or even permanent closure (Kreiss (2021)).

This unexpected and unprecedented shock to branch banking services provides us with an opportunity to study the role of banks' digital capabilities in affecting how they serve retail customers. There are numerous factors at play.

[1]See, for example, Petersen and Rajan (2002) and Keil and Ongena (2020).

[2]Branch closings can lead to persistent declines in small business lending (Nguyen (2019)) and less competitive loan markets (Bonfim, Nogueira, and Ongena (2021)). Herpfer, Mjøs, and Schmidt (2022) find evidence that reductions in travel time lower banks' transaction costs and facilitate banking relationships.

[3]See, for example, *The Economist* (2020).

[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/).

Customers facing the prospect of COVID-19 may be less willing or able to visit physical branch services, either because they want to avoid personal risk or because mobility restrictions prevent them from leaving their home or visiting bank branches. Likewise, banks may face restrictions keeping the branches open, and bank employees may prefer to work from home. Both of these demand-side and supply side effects would result in a reduction of physical branch visits and a greater shift toward digital banking since the onset of the pandemic.

We argue that banks with strong IT are better able to make this transition from in-person to digital services. Better IT allows banks to support remote work, to provide impacted customers with alternative services, or to scale up and improve existing digital infrastructure. To examine the relationship between IT and bank service provision during the pandemic, we examine a number of outcome variables assembled from various data sets, including physical bank branch visits, website traffic, SBA Paycheck Protection Program (PPP) lending to small businesses, customers' propensity to switch banks, deposit flows, as well as mobile customer reviews. Across these various outcomes, we find that better IT is associated with 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 technology usage 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, our 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 aggregate it to the bank level.[5] While this is our preferred measure, our findings are robust to other measures of IT as well.[6]

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 comes 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 and Spiegel

[5]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.

[6]In robustness checks reported in Section IA.V of the Supplementary Material, 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.

and Tookes (2021). We construct an indicator of severe mobility restrictions and find that banks with stronger IT capabilities experience significantly larger reductions in customer visits to physical branches after—but not before—the imposition of severe mobility restrictions, suggesting that better IT enables banks to better serve their customers without the need for face-to-face interaction.[7] A 1-standard-deviation increase in IT_INDEX is associated with a doubling of the effect of mobility restrictions on branch visits.

We then perform a complementary analysis of traffic to banks' websites. We use two data sources to measure bank web traffic. Our main data come from AlexaRank, which dynamically ranks global websites by their estimated traffic. This allows us to measure the relative rankings of bank websites' visitor volumes over time. While we do not see the actual volume that the ranking is based on, these rank data allow cross-bank comparisons of changes in website volumes on a weekly basis. We complement this data with a direct monthly measure of web traffic provided by SimilarWeb. Our analyses based on both data sets provide robust evidence that better IT is associated with a significantly larger increase in bank website traffic in response to mobility restrictions. The economic magnitude is large: a 1-standard-deviation increase in bank IT increases the effect of mobility restrictions on bank web traffic by 10% of the within-bank standard deviation. Overall, our findings on bank branch visits and web traffic suggest that banks with better IT more successfully shift from in-person to digital banking services during the COVID-19 pandemic.

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 "website technologies" present on banks' websites.[8] While not all technologies are equally important, having more technologies 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 1-standard-deviation increase in IT_INDEX is associated with approximately 1–2 days reduction in reaction time, depending on model specification. This suggests that banks with better IT have more sophisticated web services and adapt faster to the pandemic.

That better IT facilitates banking customers toward digital services is important in and of itself for public health reasons, but 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 Small Business Administration (SBA) PPP.[9] We consider PPP lending a good setting to test the role of IT in banks' retail business, since PPP loans are an unexpected new loan product that banks

[7]As we discuss in Section IA.I of the Supplementary Material, we construct our mobility restriction indicator based on a set of relevant restriction categories that we identify as having the most important effects on branch visits (based on a variety of statistical models).

[8]A website 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.

[9]The PPP program is the U.S. government's SME support program, structured as government-guaranteed loans distributed through the banking system.

had to set up under substantial time pressure, and during a period when both staff and customers were potentially unable to physically be in the office. These significant operational frictions may have impacted banking relationships: Prior evidence shows that bank relationships remained important for obtaining PPP loans (e.g., Li and Strahan (2021)), 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, "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 was not their primary one ("When Their PPP Loans Didn't Come Through, These Businesses Broke Up with Their Banks," *The Wall Street Journal*, July 31, 2020. Available at https://www.wsj.com/articles/when-their-ppp-loans-didnt-come-through-these-businesses-broke-up-with-their-banks-11596205736)."

We perform two analyses to test the hypothesis that higher 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 1-standard-deviation increase in IT_INDEX is associated with a 27% 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.

We also investigate the differential relation between IT and PPP performance across counties with different characteristics. First, if our results are driven by the ability of banks with good IT to better serve customers 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. This is due to the likely higher need for digital service and the possibly better ability of high-IT banks to supply digital services despite the difficulties brought about by health risks and restrictions on banks' physical operations. 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 those 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 analysis on PPP lending. 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 COVID-19. To test these predictions,

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we form a sample of PPP borrowers who were also regular SBA-loan borrowers prior to the pandemic.[10] We find that firms are more likely to switch to better-IT banks in areas harder hit by COVID-19, and in cases where their existing lenders have worse IT. This suggests that customers prefer higher-IT banks over their previous banking relationship when COVID-19 severity—a proxy for the extent of the shock on digital banking—is 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. We find that banks with stronger IT capabilities experience significantly higher increases in deposits during the first 2 quarters of 2020. This suggests that banks that are better able to serve customers during the pandemic also attract more deposits during the COVID-19 shock, consistent with the idea that customers switched their banking relationships.

Finally, to study the underlying mechanisms more directly, we collect data on customer reviews for mobile banking apps from both the Android and Apple mobile app stores. We find that the average bank receives more reviews during the pandemic period, and that these reviews have lower scores. However, relative to banks with a lower IT_INDEX, higher-IT banks receive even more reviews (implying more app downloads and usage) and relatively more favorable ratings. We also use a novel textual analysis algorithm from Facebook (Lewis, Liu, Goyal, Ghazvininejad, Mohamed, Levy, Stoyanov, and Zettlemoyer (2019) to construct additional measures from the reviews. In particular, we classify positive textual comments (e.g., easy to use, reliable, effective, or aesthetically pleasing) versus negative ones (e.g., complaints about an app not working, being slow, lacking services, or being unintuitive), and compute the fraction of negative and positive comments each bank receives. Consistent with what we find from numeric scores, the fraction of positive (negative) comments is relatively higher (lower) for higher-IT banks during the pandemic.

Overall, our results suggest that banks with stronger IT capabilities can better serve their customers during the onset of COVID-19 through digital channels. We also examine two potential interpretations of these findings. While our results might suggest that banks with better IT can better serve their customers during the pandemic, it is also possible that banks with better IT could have a more IT-savvy clientele even before the pandemic, who might be more inclined to shift toward digital services during the pandemic. Both interpretations are equally interesting but have different policy implications. While we cannot rule out either interpretation conclusively, three pieces of evidence are inconsistent with clientele sorting driving our main results. First, we examine the ex ante relationship between bank and SME customer IT before the pandemic and find no significant relationship between the two. In addition, those customer firms' own remote work decisions respond to the pandemic similarly, regardless of their banks' IT. Finally, as noted before, we find customer firms *switch* from lower-IT banks to higher-IT banks. Thus, our results are

[10]We caution that the PPP data only provide names for borrowers above a threshold size, while the SBA sample includes many very small businesses. Still, we obtain a sample of 97,758 borrowers present in both data sets.

less likely 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 during the pandemic.

We make several contributions to the literature. First, we provide evidence of the impact of technology on bank outcomes. Our setting with an unexpected shock to digital banking services allows us to partly overcome the identification challenge (i.e., the possibility that both consumer preferences and bank performance may affect investment in IT), instead of the other way around. A few other papers also study the role of bank IT during the pandemic. Closely related to our article, Core and De Marco (2023) study the impacts of bank IT capability on small business credit provision in Italy during COVID-19 and how bank IT affects the importance of local branches. The institutional features of the Italian guarantee program and the granular data enable them to examine not only the probability of lending, but also the pricing and processing time as well as the relationship between local branches and lending. In their study, Core and De Marco (2023) measure bank IT using the rating of bank mobile apps. Our article augments these discussions by utilizing the rich data sources available in the U.S., which permits us to investigate a set of other bank outcomes. Our analyses enable us to show how banks' IT affects their ability to substitute from in-person to digital banking, and how they serve customers in the retail lending and deposits markets, as well as their service quality. We also introduce a new measure of bank IT that pinpoints the specific technologies used by each bank. Overall, relying on different measures of IT and different institutional settings, these papers complement and reinforce each other in showing the role of IT in banking during a pandemic.

Second, our study is related to the literature on the interplay 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. 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, as greater fungibility between banks' online and brick-and-mortar services can reduce the economic impact of mobility restrictions and increase flexibility in unexpected situations. Despite these benefits, the variation across banks in IT and its impact imply heterogeneous economic costs of the pandemic. Finally, beyond banking, it is also likely that a relationship between IT and performance exists in other industries as well.

## II. Relevant Literature

### A. Banks, Technology, and Branches

A vast literature studies the implications of technological change on banking and the role of branch banking. For example, Petersen and Rajan (2002) find evidence of technology facilitating small business lending to increasingly distant customers.[11] 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) find incorporating bank IT helps explain bank productivity. He, Jiang, Xu, and Yin (2021) documents the relationship between bank IT investments and their usage of soft versus hard information. Pierri and Timmer (2022) find that higher pre-crisis PC adoption by banks is associated with lower levels of nonperforming loans during the financial crisis of 2008–2009. Mixed evidence of IT on bank outcomes may reflect the endogeneity between bank performance and IT investment. Thus, our study contributes evidence based on an exogenous shock to the relative attractiveness of digital services in the U.S. As mentioned previously, other work has explored the Italian loan program using different IT measures and richer loan-level data (Core and De Marco (2023)) outside the U.S. Also, Branzoli, Rainone, and Supino (2023) study the Italian loan program using a different measure of IT.

## B. Fintech and Sources of Technological Advantage

The rapid rise of technology-driven financial institutions has brought attention to the advantage that technology can provide. For example, 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.[12] In addition, whether fintech firms reach underserved clienteles and serve as complements or substitutes for traditional banking remains a debate. For example, Tang (2019) finds evidence that p2p lending serves inframarginal bank borrowers but also complements bank lending with respect to small loans. Danisewicz and Elard (2022) find that access to fintech credit reduces personal bankruptcies. Another contested issue is whether removing face-to-face interaction and moving to algorithm-based decision-making increases or decreases bias and discrimination in credit decisions. For example, Bartlett, Morse, Stanton, and Wallace (2022) and Fuster, Goldsmith-Pinkham, Ramadorai, and Walther

[11] Keil and Ongena (2020) find evidence of technological change contributing to the decrease in the number of branches. Basten and Ongena (2020) find evidence of banks using online platforms to increase geographic diversification. D'Andrea and Limodio (2023) study the introduction of high-speed internet on private-sector lending by banks. 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. Berger and DeYoung (2006) find that technological progress has facilitated banks' geographic expansion further away from parent banks. Historically, Lin, Ma, Sun, and Xu (2021) find the telegraph enabled Chinese banks to expand their branch networks from 1881 to 1936.

[12] In addition, 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. In addition, Buchak, Matvos, Piskorski, and Seru (2018) show a large factor in the rise of fintech lenders is regulatory arbitrage. They estimate that regulation accounts for 60% of shadow bank growth in mortgage lending, while technology accounts for the rest.

(2022) present contrasting studies of whether minority borrowers are likely to benefit from fintech algorithms.

Our study is unique from the fintech literature in that we focus on the technological capabilities of 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 that substantial variation in IT readiness remains among banks.

### C. COVID-19, the PPP, and the Banking Sector

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 pandemic sparked large-scale mobility restrictions across many states in early Mar. 2020. The literature has studied the effects of these restrictions on social distancing (e.g., Adalja, Toner, and Inglesby (2020) and Ru, Yang, and Zou (2021)), as well as the economic impacts on the labor market (e.g., Bartik, Bertrand, Cullen, Glaeser, Luca, and Stanton (2020a) and Humphries, Neilson, and Ulyessea (2020), household consumption (e.g., Andersen, Hansen, Johannesen, and Sheridan (2022), Baker, Farrokhnia, Meyer, Pagel, and Yannelis (2020)), and various other parts of the economy.

Most relevant to us, some of these studies focus on the PPP. On Mar. 27, 2020, the U.S. Congress passed the Coronavirus Aid, Relief, and Economic Security (CARES) Act, which included $350 billion to fund the PPP. The PPP supported 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), Branzoli et al. (2023), and Core and De Marco (2023)). Some of these studies focus on alternative lenders.[13] Finally, Fu and Mishra (2022) find evidence of a worldwide increase in bank mobile application downloads during the pandemic.

## III. Data and Methodology

### A. 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 76.4% of all parent companies with employment headcounts over 25 in the United States.[14] We use the

[13]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. Bao and Huang (2021) show that fintech lenders expand lending to constrained borrowers during the pandemic, but also experience a higher default rate subsequently. Howell, Kuchler, Snitkof, Stroebel, and Wong (2021) examine racial disparities in access to PPP loans from banks and the role of fintech lenders.

[14]To make this assessment, we compare the National Establishment Time Series database 2019 file from Dun and Bradstreet, which has been used widely in the literature. From discussions with Aberdeen, its universe of firms is based on the Dun and Bradstreet database.

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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 not having 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 digital operations is reasonable, one might be concerned about the possibility of measurement error. To mitigate such concerns, we show in the Supplementary Material 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.[15] We show that remote IT technologies (our main 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 inverse hyperbolic sine of total IT budget divided by total employees for each bank. In various analyses throughout our Supplementary Material, we show that our main results remain robust when measuring bank IT using IT_STAFF or IT_BUDGET.

While alternative measures are valuable, our count-based measures are preferable because they allow us to study the composition of technology and identify technologies that may be particularly relevant during this period. Moreover, we posit that the breadth of capabilities matters. For example, a very expensive VPN alone may be less useful than a suite of software services such as VPN, internet phones, and video conferencing software.

## B. 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. SafeGraph observes 18.75 million devices, which are 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 (e.g., Charoenwong, Kwan, and Pursiainen (2020), Weill, Stigler, Deschenes, and Springborn (2020)) and are found to be highly correlated with

[15]Examples of the remainder of the 63 categories include technologies such as workstations, phone provider, internet providers, and generic business categories.

other commonly used measures of social mobility (e.g., Jay, Bor, Nsoesie, Lipson, Jones, Galea, and Raifman (2020)).

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 the FDIC Summary of Deposits (SOD) data set to obtain branch details. 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 38,217 branches for which we can study IT and footfall. We then construct a weekly panel data set of physical branch visits at the branch level.

## C. Measuring Banks' Digital Activities

For our analysis of website traffic, we collect data from AlexaRank via the AlexaRank API. AlexaRank estimates the number of unique visits from users of their global panel who visited a site. The underlying data are sourced from website browser extensions as well as directly from websites which participate in Alexa's data collection program. AlexaRank sources its data from millions of internet users in total. The visits are converted to a ranking score, known popularly as the "AlexaRank." AlexaRank then normalizes the data using a proprietary methodology that combines average unique visits and page views per visitor over the past 3 months. In Section IA.IV of the Supplementary Material, we include a robustness analysis using alternative data from SimilarWeb, another provider of web traffic data.

Next, we obtain data on the *historical* composition of firms' websites through BuiltWith, which indexes website 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 times 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.

Finally, we collect customer review data on bank mobile apps. We collect data from the Android app store and Apple iOS app store. These data allow us to find the version of an app of a bank, if it exists. We extract the following features: the number of reviews, the average score (1–5), the fraction of reviews that are complaints based on textual analysis, and the fraction of reviews that consider the app reliable and effective based on textual analysis. To construct the last two variables, we employ a natural language algorithm open-sourced by Facebook and described by Lewis et al. (2019). We describe the data as well as this algorithm in more detail in Section IA.VII of the Supplementary Material.

## D. Bank Data

Across different analyses, we measure bank financial characteristics using FDIC call report data, including bank deposits, size (measured by the inverse hyperbolic sine of total assets), capitalization (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 in which the bank operates.

To measure banks' small business lending during the COVID-19 pandemic, we obtain loan-level data from the SBA PPP. This program, established by the CARES Act, is implemented by the SBA 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 on Apr. 3, 2020.

Our data set 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 total PPP lending. We construct a bank-county-level data set 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 pre-pandemic SME lending volume, measured as the total small business lending by the same bank to the same county in 2019 as reported under the Community Reinvestment Act (CRA).

### E. Mobility Restrictions Due to COVID-19

We obtain county-level data on mobility restrictions from Keystone Strategy, available via GitHub as well as the Spiegel and Tookes (2021) restrictions database. These data sets describe the start and end dates of various types of restrictions. However, many of the restrictions take place simultaneously, and not all of them are equally relevant to banking activities. To construct a measure of relevant mobility restriction measures by location, we use a variety of statistical models to identify those specific restrictions that *significantly* explain changes in branch visits. We describe our method of identifying these restrictions at length in Section IA.I of the Supplementary Material, as well as our validation tests for these restrictions. In brief, out of 14 different mobility restrictions, our methodology identifies three restriction categories as being most relevant in explaining branch visits, namely: restrictions on retail establishments, shelter-in-place, and social-distancing guidelines. We define a dummy variable SEVERE_RESTRICTIONS as having at least two of these three restrictions in place. This covers about 55% of the observations since March in our branch visit sample (Table 1).

## IV. Main Results

### A. Bank IT and In-Person Branch Visits

The first aspect of the pandemic that we study is a shift away from in-person banking. We first present time-series evidence. In Figure 1, we plot the average weekly bank branch visit volume for banks with above and below sample-median IT_INDEX values. Our sample period is from Jan. 2020 to Apr. 2020, focusing on

TABLE 1

Summary Statistics

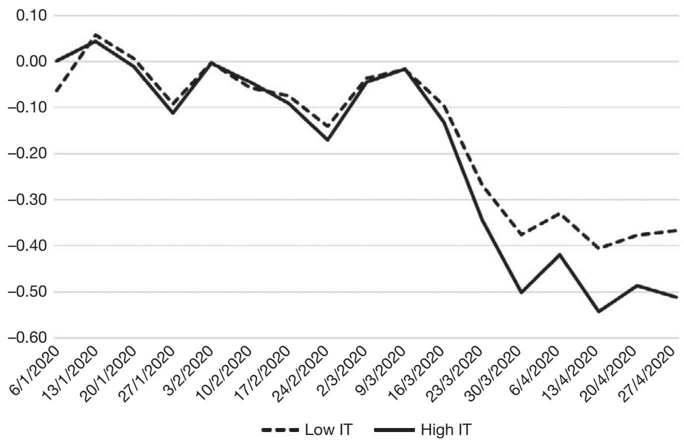
Table 1 reports the summary statistics of the main variables in each of our analyses. The variable definitions are discussed in Section III. The residual standard deviations are estimated for the residual of each variable conditional on the fixed effects used in the corresponding analysis.

| | No. of Obs. | Mean | Std. Dev. | Residual Std. Dev. | P25 | P50 | P75 |
|---|---|---|---|---|---|---|---|
| Branch Visits | | | | | | | |
| IT_INDEX | 523,844 | 5.953 | 3.028 | 0.000 | 2.934 | 6.795 | 8.633 |
| SEVERE_RESTRICTIONS | 523,844 | 0.284 | 0.451 | 0.159 | 0 | 0 | 1 |
| ihs(BRANCH_VISITS) | 523,844 | 2.751 | 1.177 | 0.446 | 1.818 | 2.776 | 3.638 |
| Web Traffic | | | | | | | |
| IT_INDEX | 29,946 | 2.384 | 1.581 | 0.000 | 1.191 | 2.000 | 3.000 |
| SEVERE_RESTRICTIONS | 29,946 | 0.278 | 0.448 | 0.168 | 0 | 0 | 1 |
| RANK ≤ 100k | 29,946 | 0.056 | 0.229 | 0.077 | 0 | 0 | 0 |
| Response Time | | | | | | | |
| IT_INDEX | 3,751 | 2.228 | 1.921 | 1.871 | 1.000 | 1.925 | 2.685 |
| ihs(WEBSITE_TECHS) | 3,751 | 5.152 | 0.589 | 0.560 | 4.754 | 5.171 | 5.545 |
| RESPONSE_TIME | 3,751 | 23.5 | 21.3 | 19.9 | 14 | 16 | 28 |
| PPP | | | | | | | |
| IT_INDEX | 30,407 | 5.124 | 2.677 | 2.369 | 2.876 | 4.577 | 7.662 |
| ihs(COVID) | 30,407 | 2.168 | 0.936 | 0.000 | 1.544 | 2.181 | 2.827 |
| ihs(PPP) | 30,407 | 14.288 | 2.489 | 2.134 | 12.407 | 14.326 | 16.088 |
| Customer Switching | | | | | | | |
| IT_INDEX_PRE_COVID_BANK | 97,645 | 5.095 | 2.913 | 2.794 | 2.251 | 4.818 | 8.032 |
| ihs(COVID) | 97,645 | 2.420 | 0.912 | 0.891 | 1.849 | 2.520 | 3.032 |
| SWITCH_TO_BETTER_IT | 97,645 | 0.180 | 0.384 | 0.380 | 0 | 0 | 0 |
| Deposits | | | | | | | |
| IT_INDEX | 29,072 | 1.850 | 1.336 | 0.000 | 1.000 | 1.667 | 2.138 |
| ihs(COVID) | 29,072 | 0.391 | 0.879 | 0.340 | 0.000 | 0.000 | 0.123 |
| ihs(DEPOSITS) | 29,072 | 13.115 | 1.417 | 0.053 | 12.185 | 12.937 | 13.809 |
| Customer Reviews | | | | | | | |
| IT_INDEX | 2,704 | 2.411 | 1.659 | 0.000 | 1.273 | 2.000 | 3.000 |
| ihs(COVID) | 2,704 | 2.597 | 2.432 | 2.422 | 0.000 | 4.327 | 4.931 |
| ihs(#REVIEWS) | 2,704 | 0.635 | 0.265 | 0.114 | 0.500 | 0.713 | 0.829 |
| SCORE ≥ 4 | 2,704 | 0.091 | 0.063 | 0.027 | 0.042 | 0.076 | 0.125 |
| COMPLAINTS | 2,704 | −0.297 | 0.260 | 0.117 | −0.441 | −0.229 | −0.112 |
| RELIABLE | 2,704 | 3.751 | 1.480 | 0.383 | 2.492 | 3.333 | 4.543 |

FIGURE 1

Branch Visits Versus Bank IT

Figure 1 plots the average weekly number of physical bank branch visits for banks with above- and below-median IT_INDEX. Both series are scaled relative to the median of the first 5 weeks of the year.



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the window before and after the onset of the pandemic in the United States.[16] The graph is normalized so that low- and high-IT banks have the same pre-pandemic median during the first 5 weeks of the year.[17] In January and February, there is no noticeable difference between high- and low-IT banks. However, a clear divergence emerges in mid-Mar. 2020, when COVID-19 cases started to increase and mobility restrictions were put in place in many communities.

We next study how in-person branch visits change in response to the introduction of mobility restrictions, and how the responses vary by banks' IT_INDEX. This analysis exploits staggered local variation in mobility restrictions, which have been shown by many prior studies to be associated with significant increases in social distancing and reduced mobility.[18] We expect mobility restrictions to result in fewer branch visits because they significantly increase customers' costs of visiting bank branches in person, as well as banks' costs of operating branch banking services. In addition, we expect mobility restrictions to have larger impact on banks with better IT, as their stronger digital capabilities may enable them to more easily substitute online services for branch services.

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

$$\begin{aligned}(1)\quad \text{ihs}(\text{BRANCH\_VISITS})_{i,t} = {} & \alpha_i + \gamma_t + \beta \text{SEVERE\_RESTRICTIONS}_{c,t} \\ & \times \text{IT\_INDEX}_j + \gamma \text{SEVERE\_RESTRICTIONS}_{c,t} \\ & + \phi \mathbf{X}_{i,t} + \varepsilon_{i,t},\end{aligned}$$

where ihs(BRANCH_VISITS)$_{i,t}$ is the inverse hyperbolic sine of the weekly number of visits at branch $i$ in week $t$. SEVERE_RESTRICTIONS$_{c,t}$ is a dummy variable indicating our measure of severe restrictions are currently in place in county $c$ where the branch is located, at week $t$. IT_INDEX$_j$ measures the ex ante IT capabilities of bank $j$ that owns the branch, and $\mathbf{X}_{i,t}$ is a vector of controls. We include branch fixed effects ($\alpha_i$), week fixed effects ($\gamma_t$), and, depending on the specification, also county linear trends or county-week fixed effects.

In Section IA.II of the Supplementary Material, we present supporting evidence that this county-level restriction indicator affords a valid difference-in-difference design. In Figure IA.1 in the Supplementary Material, we present an event-time plot using the recently proposed estimator by Borusyak, Jaravel, and Spiess (2022). We first validate the staggered effects of mobility restrictions on a significant decline of physical branch visits. We then proceed to look at the differential responses across high- and low-IT banks and show that there is a divergence in branch visits between high- and low-IT in response to local mobility restrictions.

[16]This horizon is comparable to many other papers that study the COVID-19 setting, such as Bian, Li, Xu, and Foutz (2022).

[17]We use the first 5 weeks to follow the same methodology as Google Community Mobility Reports. The patterns observed would look very similar if we instead chose the first 4 or 8 weeks.

[18]Such studies use restrictions to study the effect of moderating variables such as social connections, political affiliation, and other factors (e.g., Allcott, Boxell, Conway, Gentzkow, Thaler, and Yang (2020), Charoenwong et al. (2020), and Ding, Levine, Lin, and Xie (2020).

TABLE 2

Branch Visits During Mobility Restrictions

Table 2 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, ihs(BRANCH_VISITS) is the inverse hyperbolic sine of the number of visits recorded in SafeGraph's Places of Interest file. SEVERE_RESTRICTIONS is a dummy variable indicating severe restrictions as defined in Section IA.I of the Supplementary Material. The sample period is from Jan. to Apr. 2020. Heteroscedasticity-robust standard errors clustered by county and bank are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

| | ihs(BRANCH_VISITS) | | | | |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| SEVERE_RESTRICTIONS | −0.0798*** | −0.0348*** | −0.0760*** | −0.0351*** | |
| | (0.0093) | (0.0066) | (0.0117) | (0.0052) | |
| IT_INDEX × SEVERE_RESTRICTIONS | | | −0.0224*** | −0.0108*** | −0.0064** |
| | | | (0.0033) | (0.0026) | (0.0029) |
| Branch FE | Yes | Yes | Yes | Yes | Yes |
| Week FE | Yes | Yes | Yes | Yes | No |
| County linear trends | No | Yes | No | Yes | No |
| County-week FE | No | No | No | No | Yes |
| No. of obs. | 522,370 | 522,370 | 522,370 | 522,370 | 515,256 |
| $R^2$ | 0.8561 | 0.8606 | 0.8568 | 0.8607 | 0.8685 |

In Table 2, we present our regression analysis. The results confirm that following the introduction of severe mobility restrictions, branch visits decrease substantially more for the high-IT banks relative to low-IT ones. This is consistent with the notion that banks with better technology are less reliant on physical branches to serve their customers during the start of the COVID-19 pandemic. In terms of economic magnitudes, column 2 suggests that branch visits on average decline by 3.5% in response to severe mobility restrictions. Additionally, column 4 shows that a 1-standard-deviation-higher bank IT_INDEX almost doubles the average effect of restrictions. This effect remains robust when controlling for county-by-week fixed effects.

That branch visits drop in response to mobility restrictions could reflect both customers proactively choosing to avoid bank branches or banks simply curtailing their branch banking services. Studies like Kreiss (2021) find that branches closed at an accelerated rate during the pandemic. While we do not know precisely whether branch service hours are shortened or whether a branch is closed, we conduct two additional analyses using remote work data from Kwan and Matthies (2022) which we further describe in Section IA.III of the Supplementary Material. The basic idea is that bank employees' intensity of remote work likely reflects banks' operational changes in their brick-and-mortar branch services. First, we ask if bank employees' remote work intensity is affected by the mobility restrictions. In Panel A of Table IA.3 in the Supplementary Material, we find that employees of strong-IT banks are more able to work remotely in response to the mobility restrictions. This finding provides supporting evidence that the pandemic indeed leads to operational changes by banks. Second, we control for the remote work measure in our branch visit analysis (Panel B of Table IA.3 in the Supplementary Material). We find similar results to Table 2: controlling for our proxy of bank operational behavior (remote work), the relation between IT and mobility restrictions on bank visits remains significant. These findings provide suggestive evidence that the drop in branch visits is likely driven by a combination of both customer and bank behavior as opposed to one channel exclusively.

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## B. Bank IT and Website Traffic

We next perform a complementary analysis comprised of studying customers' online visits to banks' websites. Our main measure of bank web traffic is based on the AlexaRank, which provides an ordinal measure of the traffic volume of websites. As mentioned before, AlexaRank tracks internet traffic using a panel of internet users who have browser extensions installed which Alexa owns. This is only a fraction of the internet, and according to the data provider, websites with low levels of traffic are ranked less accurately. This makes the AlexaRank only reliable for the top 100,000 websites.[19] In light of this caveat, we define three outcome variables based on whether the AlexaRank crosses the 100,000 threshold. The three outcome variables we use are: i) a dummy indicating whether the bank's median rank within a week is in the top 100,000, ii) the percentage of days in the week the rank is in the top 100,000, and iii) a dummy for whether more than half of the days in a week are in the top 100,000. As a bank may have multiple establishments in multiple counties, we further construct a bank-level restriction measure based on banks' differential geographic exposures to the pandemic and mobility restrictions. Here, our bank-level restriction indicator equals 1 if at least half of the bank branches are located in counties where our county-level restriction indicator equals 1.[20]

Based on these measures, we test for the effect of mobility restrictions on bank website traffic, conditional on bank IT, using regressions of the following form:

$$\text{(2)} \quad \text{MEDIAN\_RANK} \leq 100\text{k}_{i,t} = \alpha_i + \gamma_t + \beta \text{SEVERE\_RESTRICTIONS}_{i,t} \times \text{IT\_INDEX}_i + \theta \text{SEVERE\_RESTRICTIONS}_{i,t} + \phi \mathbf{X}_{i,t} + \varepsilon_{i,t},$$

where MEDIAN_RANK $\leq 100\text{k}_{i,t}$ is a dummy taking the value of 1 if the median rank of the bank $i$ in AlexaRank is in the top 100,000 websites in week $t$. We can also replace this outcome variable with the other two measures of bank web traffic we introduced above. SEVERE_RESTRICTIONS$_{i,t}$ is a dummy variable taking the value of 1 if our county-level restriction measure is in place in at least half of the bank's branch locations, at week $t$. IT_INDEX$_i$ measures the pre-pandemic IT capabilities of bank $i$, and $\mathbf{X}_{i,t}$ is a vector of controls. We include bank fixed effects ($\alpha_i$) and week fixed effects ($\gamma_t$).

The results on web traffic 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. We report regression results in Table 3. The odd-numbered columns show the effect of restrictions alone. According to estimates in column 2, a bank with a 1-standard-deviation-higher IT_INDEX has a 77-BPS-higher probability of receiving higher web traffic such that the AlexaRank is above 100,000. This is about 10% of the within-bank standard

[19]For a discussion of this issue, please see https://attentioninsight.com/what-is-alexa-rank-and-its-value/.

[20]Our results are robust to alternative measures of bank-level restrictions. For example, the results remain robust if we define the bank-level restriction indicator by considering at least 25% or any branches are exposed.

TABLE 3

**Website Traffic During Mobility Restrictions**

Table 3 tests the impact of mobility restrictions on bank website traffic during the COVID-19 pandemic. The unit of observation is a bank-week. We construct three outcome variables based on whether or not the AlexaRank crosses the 100,000 threshold. This threshold is chosen because documentation suggests that AlexaRank is more reliable for the top 100,000 websites due to the sparsity of data for lower-ranked websites. MEDIAN_RANK ≤ 100_k indicates whether the bank's median rank in the week is in the AlexaRank top 100,000. %(RANK ≤ 100k) is the percentage of days in the week where the bank's rank is in the top 100,000. %(RANK ≤ 100k) ≥ 50% is a dummy indicating whether the rank is in the top 100,000 for more than half of the days during the week. SEVERE_RESTRICTIONS is a bank-level dummy indicator that equals 1 if more than half of the bank branches are located in counties with severe restrictions as defined in Section IA.I of the Supplementary Material. The sample period is from Jan. to Apr. 2020. Heteroscedasticity-robust standard errors clustered by bank are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

| | MEDIAN_RANK ≤ 100k | | %(RANK ≤ 100k) | | % (RANK ≤ 100k) ≥ 50% | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 |
| SEVERE_RESTRICTIONS | 0.0045* | 0.0039* | 0.0040*** | 0.0037** | 0.0067*** | 0.0063*** |
| | (0.0023) | (0.0022) | (0.0016) | (0.0015) | (0.0021) | (0.0020) |
| IT_INDEX × SEVERE_RESTRICTIONS | | 0.0049*** | | 0.0023*** | | 0.0040** |
| | | (0.0015) | | (0.0009) | | (0.0016) |
| Bank FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Week FE | Yes | Yes | Yes | Yes | Yes | Yes |
| No. of obs. | 29,946 | 29,946 | 29,946 | 29,946 | 29,946 | 29,946 |
| $R^2$ | 0.8880 | 0.8882 | 0.9589 | 0.9590 | 0.8920 | 0.8921 |

deviation. The results are similar when we measure relative web traffic using the other two variables mentioned above. We also present an event-study analysis in Figure IA.2 in the Supplementary Material. This figure suggests a larger jump in web traffic by high-IT banks at the onset of mobility restrictions.

To address the concern that the web traffic analysis is based on a rank measure that does not capture the absolute changes in web traffic volume, we conduct a robustness analysis using an alternative source of web traffic data provided by SimilarWeb, which uses similar data collection methodologies as AlexaRank, but produces visitor counts instead of a rank variable although only at the monthly level. We report these analyses in Table IA.4 in the Supplementary Material. This test is relatively less powerful, as analysis at the monthly level obscures variation across banks in terms of how quickly they were impacted by mobility restrictions during the middle of March. Still, like with our AlexaRank analysis, we find that high-IT banks receive more web traffic in response to mobility restrictions.

To provide further support for the above findings, we next check whether our IT_INDEX is correlated with characteristics of bank websites, which likely play 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 in 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.

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TABLE 4

Website Characteristics and COVID-19 Response Time

Table 4 characterizes the relation between IT_INDEX and website characteristics. The unit of observation is a bank. ihs(WEBSITE_TECHS) is the inverse hyperbolic sine of the number of observed BuiltWith technologies by Feb. 2020. RESPONSE_TIME is measured as the number of days from Mar. 13, 2020 (the declaration of national emergency) that it took for the bank to mention COVID-19 on its website as reported by BuiltWith. Negative coefficients imply earlier responses. *Bank controls* include size (measured by the inverse hyperbolic sine of total assets), capitalization (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. In columns 3 and 4, we also include fixed effects for decile bins of average COVID cases per capita across each bank's branch network, which controls for the cross-bank variation of COVID severity that might affect banks' speed of response. Heteroscedasticity-robust standard errors clustered by bank are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

| | ihs(WEBSITE_TECHS) | | RESPONSE_TIME | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| IT_INDEX | 0.1148*** | 0.0589*** | −0.9771*** | −0.3911** |
| | (0.0072) | (0.0054) | (0.1870) | (0.1935) |
| Bank controls | No | Yes | No | Yes |
| HQ state FE | Yes | Yes | No | No |
| HQ state × COVID decile FE | No | No | Yes | Yes |
| No. of obs. | 3,750 | 3,741 | 3,651 | 3,642 |
| $R^2$ | 0.2305 | 0.4574 | 0.1373 | 0.1735 |

One particularly interesting aspect that BuiltWith tracks is the time when websites mention the COVID-19 pandemic. We define a response time variable as the number of days between Mar. 13— when a national emergency was declared —and the first time the bank website mentions the pandemic. Columns 3 and 4 in 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 1-standard-deviation increase in IT_INDEX is associated with approximately 1–2 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.

## C. Bank IT and PPP Lending

### 1. PPP Loan Volumes

Next, we focus on the amount of small business loans originated under the SBA PPP. This can be viewed as the extensive margin of PPP lending – we later examine the intensive margin in 2. 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:

$$\text{ihs}(\text{PPP}_{i,c}) = \alpha_c + \gamma_{hq} + \beta \text{IT\_INDEX}_i + \phi \mathbf{X}_{i,c} + \delta \mathbf{X}_i + \varepsilon_{i,c}, \tag{3}$$

where $\text{ihs}(\text{PPP}_{i,c})$ is the inverse hyperbolic sine of the volume of PPP loans originated by bank $i$ in county $c$. $\mathbf{X}_{i,c}$ is a vector of pre-pandemic bank-county level controls, including the inverse hyperbolic sine of the 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 in the year before the pandemic. $\mathbf{X}_i$ is a vector of bank characteristics, including bank size (measured by the inverse hyperbolic sine of total assets), capitalization (measured by both equity/asset ratio

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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. $\alpha_c$ refers to the county fixed effects, and $\gamma_{hq}$ is a dummy variable indicating the state of the bank headquarter. 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 columns 1 and 2 in Table 5. Across all the specifications, 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 for deposits of the same bank in the same county, which control for the ex ante market share of each bank in each market. The effect is economically significant: According to the point estimate in column 2 (e.g., a 1-standard-deviation increase in bank IT leads to a 27% increase in PPP lending to small businesses), which accounts for about 12.5% of the residual standard deviation of PPP lending.

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 with worse outbreaks of COVID-19. There are two main reasons for this. First, although PPP applications were filed mostly online, loan officers and other branch personnel were often involved in screening loans or assisting customers in the application process.[21] In counties with larger outbreaks of COVID-19, in-person supports to customers and offline work by loan officers was more difficult, and thus stronger-IT banks had greater advantages processing and screening PPP applications through their digital infrastructure. Second, areas with high COVID-19 numbers saw greater loan demand (e.g., Bartik, Cullen, Glaeser, Luca, Stanton, and Sunderam (2020b)), and banks likely suffered longer backlogs especially if they had poorer IT.[22] Customers, either experiencing or anticipating slow response times from worse-IT banks, would be likelier to switch to banks with better IT, as slow processing means longer waiting time and even a lower likelihood of obtaining a loan, given that the program has a limited amount of funds.

To test this prediction, we study the impact of bank IT conditional on the severity of the outbreak. We perform a regression analysis including an interaction between the IT_INDEX and the inverse hyperbolic sine of the number of confirmed COVID-19 cases per thousand people in the county. The result is shown in column 3 in Table 5. According to the estimates, if the number of confirmed COVID-19 cases increases by 1-standard-deviation, the estimated effect of bank IT is about 17% larger compared to the average effect.

[21]For example, when Pinnacle Bank started to accept PPP loan applications, it explicitly advised its customers that “in order to apply, contact your local branch or loan officer.”

[22]Anecdotally, the PPP loan processing time could reach as high as several weeks if the applicants are processed manually, but only a few days or even shorter when the process is automated. For example, see https://markets.businessinsider.com/news/stocks/automation-anywhere-launches-ai-powered-banking-bot-to-expedite-sba-loan-processing-from-3-weeks-to-3-days-1029098646.

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TABLE 5

**PPP Lending During the Pandemic**

Table 5 estimates the effect of bank IT on PPP lending to small businesses. The unit of observation is a bank-county. The dependent variable is ihs(PPP), the inverse hyperbolic sine of the amount of PPP loans originated by each bank in each county. ihs(COVID) is the inverse hyperbolic sine 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 ex ante SME lending across banks in the county. *Bank controls* include size (measured by the inverse hyperbolic sine of total assets), capitalization (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. *Bank-county controls* include ihs(CRA) and ihs(DEPOSITS). ihs(CRA) is the inverse hyperbolic sine of the pre-pandemic amount of CRA small business lending by the same bank to the same county. ihs(DEPOSITS) is the inverse hyperbolic sine of the amount of pre-pandemic deposits of the bank in the same county. Heteroscedasticity-robust standard errors clustered by county and bank are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

| | ihs(PPP) | | | | |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| IT_INDEX | 0.1530*** | 0.0993*** | | | |
| | (0.0298) | (0.0308) | | | |
| IT_INDEX × ihs(COVID) | | | 0.0184*** | | |
| | | | (0.0061) | | |
| IT_INDEX × INTERNET_USE | | | | 0.0098*** | |
| | | | | (0.0025) | |
| IT_INDEX × HHI | | | | | −0.2950*** |
| | | | | | (0.0672) |
| Bank-county controls | No | Yes | Yes | Yes | Yes |
| Bank controls | No | Yes | No | No | No |
| HQ state dummy | Yes | Yes | Yes | Yes | Yes |
| County FE | Yes | Yes | Yes | Yes | Yes |
| Bank FE | No | No | Yes | Yes | Yes |
| No. of obs. | 30,166 | 30,166 | 30,163 | 30,130 | 30,163 |
| $R^2$ | 0.2852 | 0.6521 | 0.7077 | 0.7082 | 0.7080 |

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 result, shown in column 4 in Table 5, suggests 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 those 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. Column 5 shows 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 these specifications control for both the county and bank fixed effects. Thus, a stronger IT capability can have a stronger effect on PPP lending in counties with a greater COVID-19 shock, better internet, and greater banking competition. These within-bank comparisons also help us further rule out the concern that our results might be driven by unobserved bank characteristics that are correlated with bank IT.

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TABLE 6

Likelihood of Customer Switching Banks for PPP Loan

Table 6 estimates small businesses' likelihood of switching to better IT banks during the pandemic. The sample of small businesses are those taking SBA 7a loans between 2011 and 2019 which we can match with the Aberdeen Computer Intelligence database. The dependent variable is a dummy taking the value of 1 if the borrower's PPP lender has a higher IT_INDEX than this same borrower's pre-COVID relationship bank (via SBA loans). Heteroscedasticity-robust standard errors clustered by borrower county are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

| | SWITCH_TO_BETTER_IT | | |
|---|---|---|---|
| | 1 | 2 | 3 |
| ihs(COVID) | 0.0128*** | 0.0215*** | 0.0219*** |
| | (0.0041) | (0.0049) | (0.0045) |
| IT_INDEX_PRE_COVID_BANK | | −0.0262*** | −0.0262*** |
| | | (0.0017) | (0.0016) |
| ihs(COVID) × IT_INDEX_PRE_COVID_BANK | | | −0.0058*** |
| | | | (0.0013) |
| Industry (NAICS) FE | Yes | Yes | Yes |
| No. of obs. | 97,548 | 97,548 | 97,548 |
| $R^2$ | 0.0209 | 0.0568 | 0.0584 |

## 2. 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 when choosing lenders that provide PPP loans. This can be viewed as the intensive margin of PPP lending, whereas our previous analysis in Table 5 might be viewed as the extensive margin. 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 ex ante and the PPP program ex post. We match borrowers across these two samples and form a panel of 97,758 firms that are PPP borrowers in 2020 and SBA borrowers between 2011 and 2019.[23] To identify borrowers that switch banks, we look at firms that take PPP loans who also have an SBA loan, and we define a binary outcome variable that takes the value of 1 if the firm changes to a bank with a higher IT_INDEX than its pre-COVID-19 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-19 lender.

Our results are shown in Table 6. Consistent with our 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. Controlling for the IT strength of the pre-COVID bank, the estimates in column 2 suggest that a 1-standard-deviation increase in the severity of COVID-19 would result in an approximately 2-percentage-point-higher likelihood that a borrower switches to a stronger-IT bank after the onset of the pandemic. This increase is roughly 11% against the mean probability of switch (2/18). The interaction term in column 3 further suggests that, given a 1-standard-deviation increase in COVID severity, if a borrower is already related to a bank with a 1-standard-deviation-higher IT_INDEX, then the probability that

[23]The public data of PPP lending only name borrowers with borrowing amounts above $150,000, while normal SBA loans target relatively smaller borrowers. Thus, the intersection of the two sets of firms only represents a fraction of the universe.

TABLE 7

Deposits During the Pandemic

Table 7 estimates the relation between bank IT and deposits during the pandemic. The dependent variable is ihs(DEPOSITS), the inverse hyperbolic sine of the quarterly bank-level deposits. The sample period is from 2019 Q1 to 2020 Q2. Q1_2020_ONWARD is a dummy variable that equals 1 for the first 2 quarters of 2020. *Bank controls* include size (measured by the inverse hyperbolic sine of total assets), capitalization (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. Industry (NAICS) refers to the industry classifications from the North American Industrial Classification system. Heteroscedasticity-robust standard errors clustered by bank are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

| | ihs(DEPOSITS) | | | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| IT_INDEX × Q1_2020_ONWARD | 0.0066*** | 0.0033*** | | |
| | (0.0010) | (0.0006) | | |
| IT_INDEX × ihs(COVID) | | | 0.0028*** | 0.0012*** |
| | | | (0.0005) | (0.0003) |
| ihs(COVID) | | | 0.0094*** | 0.0037*** |
| | | | (0.0014) | (0.0012) |
| Bank controls | No | Yes | No | Yes |
| Bank FE | Yes | Yes | Yes | Yes |
| Quarter FE | Yes | Yes | Yes | Yes |
| No. of obs. | 29,062 | 27,472 | 29,062 | 27,472 |
| $R^2$ | 0.9986 | 0.9993 | 0.9986 | 0.9993 |

this borrower switches to another bank with even higher IT would be 1.5-percentage-points lower relative to a borrower related with an average-IT bank. Taken together, the results suggest that a stronger COVID-19 shock leads to a greater probability of switching to a bank with better IT.

## D. Bank IT and Deposits

Next, we examine the dynamic of bank deposits over the first 2 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:

$$\text{(4)} \qquad \text{ihs}(\text{DEPOSITS})_{i,t} = \alpha_i + \gamma_t + \beta \text{IT\_INDEX}_i \times \text{Q1\_2020\_ONWARD} + \phi \mathbf{X}_{i,t-1} + \varepsilon_{i,t},$$

where ihs(DEPOSITS)$_{i,t}$ is the inverse hyperbolic sine of the deposits of bank $i$ in quarter $t$. $\alpha_i$ and $\gamma_t$ are bank and quarter fixed effects. Q1_2020_ONWARD is a dummy variable that equals 1 for the first 2 quarters in 2020 (the first wave of COVID-19), and 0 otherwise. $\mathbf{X}_{i,t-1}$ is a vector of lagged controls, including bank size (measured by the inverse hyperbolic sine of total assets), capitalization (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. Columns 1 and 2 compare deposits of banks with different IT levels in the first 2 quarters of 2020 (the first wave of COVID-19) versus those in 2019, with column 2 including bank controls. Columns 3 and 4 focus on the interaction between IT_INDEX and the inverse hyperbolic sine of COVID-19 cases. Both analyses show that better bank IT is associated with a significantly

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greater increase in deposits during the onset of the pandemic. During the first 2 quarters of 2020, a 1-standard-deviation-higher bank IT explains higher deposit flows equivalent to 8.3% of the residual standard error.[24] Moreover, banks with stronger IT also see a higher deposit sensitivity to COVID-19. We present a graphical version of this result in Figure IA.3 in the Supplementary Material. This figure reveals that a gap in deposit levels between banks with high versus low IT is insignificant before the pandemic but becomes statistically and economically significant starting in 2020.

### E. Alternative IT Measures and Restrictions Measures

We conduct a series of robustness analyses to mitigate measurement concerns regarding how we construct the bank IT_INDEX and mobility restrictions. First, in Section IA.V of the Supplementary Material, we repeat 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, when we include both the main IT measure and IT_INDEX_OTHER simultaneously in our regression, our main measure is stronger in nearly all analyses, which further corroborates that our main IT_INDEX reflects the technologies that are most relevant for our analysis. This test also helps mitigate concerns of omitted variables. If IT were correlated with other unobserved characteristics, it is less clear why such characteristics would be specifically correlated with our specific 14 technologies which are highly relevant to remote operations. Second, our results remain similar when we measure bank IT using IT_STAFF, the number of IT staff relative to the total number of employees, which reflects a bank's stock of technology labor force or IT_BUDGET, the log amount of IT budget per employee, which reflects a bank's financial investment in technology.

Second, we show that our results are not sensitive to how we classify "severe" mobility restrictions. In Section IA.VI of the Supplementary Material, we measure restrictions by simply counting the number of restrictions in place instead of defining a dummy variable indicating whether restrictions are above a high threshold. Our results indicate that higher restriction counts relate to statistically significant drops in footfall and jumps in web traffic.

## V. Additional Analysis

### A. Customer Reviews

Our previous results suggest that banks with a higher IT_INDEX shifted operations to digital channels faster, resulting in more deposit inflow and small business loan volumes. These results are financial outcomes, which we believe could stem from high-IT banks being able to provide higher-quality services to customers during the pandemic. To test this more directly, we collect information about customer satisfaction with digital banking services as expressed through

[24]The standard deviation of bank IT is 1.34 in this sample, while deposit growth has a within-bank residual standard error of 0.053.

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TABLE 8
Customer Reviews

Table 8 presents an analysis of customer reviews. We obtain mobile app reviews from the Google Playstore and Apple App Store and process them using NLP algorithms outlined in Section IA.VII of the Supplementary Material. The pre-period is from Mar. to Dec. 2019 and the post-period is the same period in 2020. The dependent variable is shown above each column. ihs (#REVIEWS) is the inverse hyperbolic sine of the number of customer reviews. SCORE $\geq 4$ is the fraction of ratings scoring at least 4 out of 5. COMPLAINTS is the fraction of reviews indicating complaints. RELIABLE is the fraction of reviews conveying the feeling that the application is effective. In Panel A, POST is a dummy indicating the period of 2020. In Panel B, ihs(COVID) refers to the inverse hyperbolic sine of the average number of cases per capita across bank branches by the end of 2020. *Bank controls* include size (measured by the inverse hyperbolic sine of total assets), capitalization (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. Heteroscedasticity-robust standard errors clustered by bank are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

| | ihs(#REVIEWS) | SCORE $\geq$ 4 | COMPLAINTS | RELIABLE |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| *Panel A. Two-Period Analysis* | | | | |
| IT_INDEX × POST | 0.0337*** | 0.0072** | −0.0018** | 0.0073** |
| | (0.0123) | (0.0034) | (0.0008) | (0.0034) |
| POST | 0.1753*** | −0.0568*** | 0.0140*** | −0.0732*** |
| | (0.0473) | (0.0153) | (0.0038) | (0.0156) |
| Bank controls | Yes | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes | Yes |
| No. of obs. | 2,194 | 2,194 | 2,194 | 2,194 |
| $R^2$ | 0.9385 | 0.8237 | 0.8084 | 0.7420 |
| *Panel B. COVID-19 Exposure* | | | | |
| IT_INDEX × ihs(COVID) | 0.0075*** | 0.0015** | −0.0004** | 0.0015** |
| | (0.0026) | (0.0007) | (0.0002) | (0.0007) |
| ihs(COVID) | 0.0318*** | −0.0117*** | 0.0030*** | −0.0156*** |
| | (0.0097) | (0.0031) | (0.0008) | (0.0032) |
| Bank controls | Yes | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes | Yes |
| No. of obs. | 2,194 | 2,194 | 2,194 | 2,194 |
| $R^2$ | 0.9386 | 0.8238 | 0.8105 | 0.8022 |

mobile phone app reviews. Mobile app reviews are a major source of data that we can use to directly measure the quality of a bank's online services.

We collect over 2.4 million mobile app reviews from the Apple and Google mobile application stores. We aggregate these reviews into a two-period panel and compare banks' app reviews from Mar. to Dec. 2020 versus the same period in 2019. We conduct a two-period test here because there may be a lag between when a person downloads an app and when they review said app. A user may only review an app after using it for a while. For example, a user might feel compelled to review the app when the app does not work for a specific transaction, which might occur several months or even longer after installing an app.

We construct four outcome variables: the inverse hyperbolic sine of the count of reviews, the fraction of reviews with four stars or greater (following Core and De Marco (2023)), the fraction of textual comments that convey complaints, and the fraction of comments which describe the app as "reliable." The last two measures are computed based on a state-of-the-art natural language processing algorithm recently open-sourced by Facebook, called the BART Natural Language Inference model. Some apps are very sparsely rated (or the app store does not return a large number of reviews), and thus we require apps to have at least three reviews in both periods to qualify for our analysis. We further describe our data collection process as well as the textual analysis in Section IA.VII of the Supplementary Material.

We present our results in Table 8. We first describe Panel A, which simply compares banks before and after the pandemic. After the COVID-19 pandemic begins, customers of banks issue a greater number of reviews relative to 2019, and the increase in the number of reviews is greater for high-IT banks. These results likely imply more app downloads and/or usage for these banks, and in that sense concur with our earlier findings that online traffic increases in response to the pandemic, and that high-IT banks especially attract more customers to digital channels. Meanwhile, for the average bank, the fraction of high scores decreases on average, likely because new mobile customers are more demanding of mobile apps or more issues are detected when customers start using mobile apps more intensively during the pandemic period. However, the interaction term suggests that relatively speaking, despite more negative customer reviews for the average bank, high-IT banks receive a higher fraction of above-4 scores. The results are robust if we measure the reviews using the fraction of positive or negative textual comments. Finally, Panel B of this analysis suggests that these results also obtain if we compare across banks with different degrees of exposure to COVID-19. Overall, these results provide direct evidence that high-IT banks are perceived by customers to provide higher-quality service after the onset of the pandemic.

## B. Customer IT Preferences and Banks' IT Ability

Our article suggests that banks with better IT had a superior ability to operate during the pandemic. Alternatively, another plausible interpretation is that high-IT banks might potentially draw in an IT-savvy clientele even prior to the pandemic, and such IT-savvy customers may shift their banking activity toward digital channels faster in response to the pandemic, irrespective of the bank's IT capability. Both mechanisms are interesting, but provide different interpretations for policymakers.

To assess this demand-centric view, we test whether clients who are more technologically sophisticated tended to choose to work with banks with better IT before the pandemic. We test this using Small Business Administration (SBA) 7a loan data to identify pre-pandemic lending relationships between SME customers and banks. We match SBA borrowers and lender banks to Aberdeen and compute the same IT_INDEX for SMEs as before. We are able to obtain the IT information for both the lenders and borrowers for 94,150 SBA borrowers between 2011 and 2019.[25]

The results are shown in Panel A of Table 9. We do not find a positive relationship between customer IT and bank IT in any of our regressions. Hence, our findings that high-IT banks can better provide credit to SMEs through PPP loans are not likely explained by their clientele's relative familiarity with digital technology. This finding complements our previous finding that customers "switched" toward high-IT banks. It implies that customers did not seek out banks with good IT systems before the pandemic, but began to do so during the pandemic.

[25]Comparing Aberdeen, which is based on Dun and Bradstreet Data, to the NETS data, we find that Aberdeen provides broader coverage of larger establishments. Thus, our matched sample is more concentrated on the relatively larger SMEs.

TABLE 9

Bank IT Versus Customer IT

In Table 9, Panel A shows the pre-pandemic relationship between bank and customer IT. The dependent variable is the IT_INDEX of the SME customer who took SBA loans between 2011 and 2019, and the independent variable is the IT_INDEX of the corresponding SBA lender. Loan controls include the inverse hyperbolic sine of loan size and the number of jobs the borrower claims to support with the loan, loan term, interest rate, and a dummy for whether the borrower is a corporation. Panel B examines whether bank IT explains the customers' response to COVID-19 as evidenced by their propensity of remote work. The dependent variable is the estimated fraction of firm employees working remotely that week. The sample period is from Jan. to Apr. 2020. IT_INDEX_BANK and IT_INDEX_CUSTOMER are the IT_INDEX of the lending bank and the SME customer who had a borrowing relationship with the bank before the pandemic. SEVERE_RESTRICTIONS is our dummy restriction measure for the customer's county. Heteroscedasticity-robust standard errors clustered by customer county-bank (Panel A) or customer county (Panel B) are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

*Panel A. Customer Versus Bank IT (Prepandemic)*

| | IT_INDEX_CUSTOMER | | | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| IT_INDEX_BANK | −0.0091<br>(0.0071) | −0.0021<br>(0.0071) | −0.0082<br>(0.0066) | −0.0014<br>(0.0069) |
| Loan controls | No | Yes | No | Yes |
| County FE | No | No | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes |
| No. of obs. | 94,038 | 94,038 | 93,631 | 93,631 |
| $R^2$ | 0.2430 | 0.2458 | 0.2708 | 0.2735 |

*Panel B. Customer Firms' Working from Home Behavior*

| | CUSTOMER_REMOTE_WORK | | |
|---|---|---|---|
| | 1 | 2 | 3 |
| SEVERE_RESTRICTIONS | 0.0052***<br>(0.0019) | | |
| IT_INDEX_CUSTOMER × SEVERE_RESTRICTIONS | | 0.0090***<br>(0.0005) | |
| IT_INDEX_BANK × SEVERE_RESTRICTIONS | | | 0.0004<br>(0.0003) |
| Firm FE | Yes | Yes | Yes |
| Week FE | Yes | No | No |
| County-week FE | No | Yes | Yes |
| No. of obs. | 1,078,918 | 1,071,608 | 1,071,608 |
| $R^2$ | 0.5919 | 0.6040 | 0.6036 |

In addition, we show in Panel B of Table 9 that customers of ex ante high-IT banks do not exhibit stronger responses to the pandemic in their internal operations. Using a firm-level, big-data-based measure of remote work developed by Kwan and Matthies (2022), we show that although a firm is more likely to adopt remote work when COVID-19 is more severe in the local area, the firm responds to COVID-19 similarly, regardless of the lending banks' IT_INDEX. This finding further suggests the bank IT_INDEX is not picking up a bank's tech-savvy clientele.

One potential concern is that we might not be capturing the impact of IT but rather of a characteristic with which IT is highly correlated. 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. In addition, as we showed before, it is specifically the 14 remote technologies we study that show strong correlations to bank outcomes during the pandemic. Such a characteristic that is not technology would also have to become important in a way that matches the timing of mobility restrictions in a county in driving fewer branch visits and more web 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, and be correlated with information and internet technology, but not be IT itself. While we cannot rule out all omitted variables, it seems highly likely that IT is not merely a proxy for some omitted variable.

## VI. Conclusion

We find that banks' IT capabilities affect their ability to serve customers during 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 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 reduce their vulnerability to extreme shocks such as the COVID-19 pandemic. The latter point might also have important policy implications for the stability of the financial system more broadly. However, the empirical relationship between IT and banking activities observed today suggests that variation among banks remains substantial—and that there is less-than-complete readiness in the U.S. banking sector.

## Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109023000662.

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