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Bank Technology and the COVID-19 Pandemic *

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Abstract

We examine how banks' technological investments affected their ability to maintain or expand their business in the unprecedented economic recession associated with the COVID-19 pandemic. A one standard deviation increase in our financial technology measure, which describes a bank's coverage of products installed at nonbank fintech firms, is associated with an 8.7 percentage point increase in Paycheck Protection Program (PPP) loan volume in 2020Q2. Furthermore, advanced technology enables banks to supply PPP loans outside of their branch market area, though this more geographically dispersed lending does not crowd out in-market lending. Thus, technology-intensive banks, which seem to operate as a hybrid between physically-based traditional banks and less physically-based nonbank fintech lenders, can compete effectively for financial products that are less reliant on a relationship lending model.

Keywords: Banking, Fintech, Technology, Paycheck Protection Program, COVID-19

JEL Codes: G21, G23, O3

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I. Introduction

The conventional view on the comparative advantage of small banks' business models centers on relationship lending. In that narrative, small banks' structures enable them to acquire soft information about borrowers' creditworthiness that is not easily gleaned from a loan application. In contrast, large banks - through economies-of-scale - and financial technology firms - through innovations in technology - have comparative advantages in the processing of a larger volume of loans based on hard information. Consistent with theories of relationship lending, as of year-end 2019, banks' with less than $10 billion accounted for 31.6 percent of the industry aggregate of small-loans to businesses even though the same banks comprised only 15.2 percent of total industry assets.[1] Yet, increases in data availability, advances in statistical classification methods to identify risk, greater computational power, and the rise of financial technology firms have the potential to erode the benefits that smaller banks derive from their comparative advantage in soft information gathering.

Launched in the early weeks of the onset of the 2020 COVID-19 pandemic in the United States, Paycheck Protection Program (PPP) loans are precisely the information-insensitive, transactional loans that extant theories suggest are the province of larger banks and technology firms. In particular, the Small Business Administration (SBA) guaranteed the full outstanding balance of PPP loans and that guarantee was itself backed by the full faith and credit of the United States: soft information on creditworthiness provided no comparative advantage to lenders. Furthermore, because funds were potentially limited and due to pressure from borrowers, PPP lending volume depended on rapid processing of application materials. However, the 40.7 percent share of PPP lending volume and 45.1 percent share of total PPP loans made by banks with less than $10 billion as of June 2020 was not only larger than their market share in assets, but also an even greater share of PPP lending than their collective prior small business loan portfolio would suggest.[2] Therefore, while relationship banking

[1]Source: Call Reports. Small loans to businesses are defined as those with less than $1 million at issuance, as measured on Call Reports. Small loans are often used as a proxy for small-business lending (see Cortés et al. (2020)) though Federal Deposit Insurance Corporation (2018) notes important limits to its interpretation for that purpose.

[2]Source: Call Reports.

may have played a role in facilitating banks' PPP lending through pre-existing relationships (see Li and Strahan (2020)), it is difficult to reconcile relationship lending with the excess representation of smaller banks in the information-insensitive, transaction-based PPP loan market.

The rapid onset of the pandemic and the demands on banks' technological infrastructure to provide funding through PPP suggest that many small banks' were not well-equipped to provide funding. As a June 10, 2020 American Banker article argues, "[w]hen the Small Business Administration rolled out its Paycheck Protection Program, it set off a fire drill of sorts among bank technology executives, who had to quickly figure out how to accept applications from borrowers and load them into the SBA's system before the money ran out."[3] A March 19, 2020 American Banker article reports that "digial usage is rising alongside the proliferation of the virus. In some cases, it is surging."[4] Technology reports cite increased use of process automation, natural language processing, and machine learning tools to improve speed of operations at banks.[5] Together, these articles suggest that banks with stronger technology were better positioned to take advantage of the unprecedented financial stimulus associated with the economic fallout of the novel coronavirus.

In this paper, we use evidence from the PPP to demonstrate that technology varies widely across smaller and mid-sized banks and is a significant component in the average bank's ability to support information-insensitive, transaction-based lending. Unlike relationship lending, transaction-based lending does not rely on knowledge about borrowers that results from close physical proximity. Consequently, we expect that technology-based lenders lend over a more diffuse geography given a particular number of loans than do lenders with a physical presence. While many banks invested in technology and developed partnerships during the pandemic, we expect that those with pre-existing investments would be the most knowledgable and best positioned for the demands of remote access. We distinguish high-technology banks from low-

[3] Crosman, Penny. "The tech Sunrise Banks used to quickly dole out PPP loans." *American Banker*. 10 Jun. 2020.

[4] Dobbs, Jim. "Coronavirus throws digital banking into the crucible." *American Banker*. 19 Mar. 2020.

[5] Wolfgruber, Marlene. "Banks Turn to Automation to Speed SBA PPP Loan Process." *CMSWire* June 12, 2020.

technology banks by computing a Fintech Similarity Score (FSS), which measures a banking institution's pre-pandemic coverage of the technology products at a typical nonbank fintech firm (we assume that fintechs are at the forefront of innovation in financial services). Our primary measure of geographic lending concentration is a Herfindahl-Hirschman Index (HHI) of lender-level PPP county-loan concentration (discussed further below).

To provide an overview of how technology facilitates diffuse lending, Figure I plots kernel densities of the residuals from a lender-level OLS regression of county-loan HHI on a quadratic expression of log PPP loans (to control for loan volume) for lenders with at least 500 loans. We plot residuals for nonbank fintech firms, large banks (greater than $50 billion in assets as of year-end 2019), high-technology (top five percentile FSS) banks between $1 billion and $10 billion in assets and low-technology (lower 50th percentile FSS) banks between $1 billion and $10 billion in assets. Higher density on the left side of the graph indicates that conditional on the number of loans, loans tend to be more geographically dispersed for a given lender type. Conversely, higher density on the right side of the graph indicates that conditional on the number of loans, PPP loans tend to be more geographically concentrated for a given lender type. Fintech firms (discussed further below) have the most geographically dispersed loan portfolios given the number of PPP loans. Large banks, which tend to operate large branching networks that are expected to produce some ties between lending and their physical presence, are more concentrated than fintechs, which are thought to operate without a comparable physical presence. Banks between $1 billion and $10 billion and in the bottom 50th percentile FSS are far more geographically concentrated than fintech firms given the number of PPP loans issued. Perhaps more surprising is that technology-heavy banks (top fifth percentile) with between $1 billion and $10 billion in assets not only lend more diffusely than large banks, but also lend nearly as diffusely as fintechs. Through the remainder of this paper, we explore the margins along which technology explains differences in bank PPP outcomes.

Financial technology and its role in the financial landscape is prevalent in discussions in the academic literature,[6] popular press,[7], and regulatory communities.[8] From June 2010 to June 2019, the number of commercial bank branches declined by 6.3 percent (from 82,011 to 76,837) even as total commercial bank assets grew 22 percent (43 percent nominal growth). In this way, banks transitioned from a physical branch model toward one using information technology and online platforms (see Vives (2019)). Yet, in small business lending before the pandemic, personal contact had remained central to the banking business model, with only limited competition from fintech firms. The FDIC's 2018 Small Business Lending Survey Federal Deposit Insurance Corporation (2018) finds that only 11.2 percent of small banks and 22.8 percent of large banks allowed small business borrowers to apply online (as opposed to at a branch, by telephone, or on-site). Almost half of large banks, but only one in ten small banks, considered nonbank fintech firms to be a frequent competitor, with neither size class of banks considering nonbank fintechs to be a top competitor. Thus, whether the average bank could be competitive in technology-based lending remains an open question.

Among the largest challenges to examining the role of financial technology in the banking industry is the measurement of technology itself. Toward this end, we construct a novel measure of financial technology using product installation data from the Aberdeen Technology Data Cloud (hereafter Aberdeen). FSS captures the substance of technology investment more so than the scale. To feature these substantive differences, we also create component measures for a bank's similarity to fintech firms within various categories of technology (e.g. hardware and software). Banks may access technology along other dimensions, for example, in partnerships or contracting arrangements with technology providers. In robustness checks, we show that our results hold when we use alternative measures of bank technology based upon expense information available in quarterly financial statements (Call Reports). We also show that while FSS is correlated with measures of technological investment from Call

[6]See Thakor (2020), and references therein.

[7]E.g., Verhage, Julie and Jennifer Surane. "Big Tech Is Coming for Banking: Experts Predict Fintech's 2020." *Bloomberg*, 23 Dec. 2019.

[8]E.g., "The Federal Reserve has committed substantial staff resources to assessing financial innovation related to our policy and regulatory responsibilities." Statement for the Record of Staff of the Board of Governors of the Federal Reserve System, U.S. House of Representatives, 25 June 2019.

Reports, it appears to capture some distinct aspects of technology.

For our empirical analysis, we examine whether technology, as of 2019, plays an important role in understanding the average banks' PPP lending outcomes in the second quarter of 2020. We find that our FSS technology measure is strongly associated with more intensive and more geographically diffuse PPP lending, all while controlling for an array of 2019 balance sheet variables (e.g. bank size). Our finding of technology reducing concentration holds even after controlling for the geographic concentration of a bank's deposits and small business lending in 2019. We also find broadly similar results when substituting Call Report-based technology measures, which capture different aspects of technology. Thus, technology appears to facilitate less geographically concentrated PPP lending.

Our results suggest that tech-heavy banks appear to operate in the competitive landscape between fintech firms and traditional banks. While the physical presence of banks played an important role in small business lending (as in Bolton, Freixas, Gambacorta, and Mistrulli (2016)), we provide evidence that technological investments of banks enabled banks to operate more similarly to fintechs. We compare the PPP lending profile of nonbank fintechs to banks, segmented according to our technology measures. In a result that parallels Figure I, we find that banks with technological profiles similar to fintechs issued PPP loans at quantities and levels of geographic concentration more similar to the nonbank fintechs than other banks. Conditional on the quantity of loans, we find that the difference in geographic loan concentration between banks and nonbank fintechs is reduced by approximately 40 percent when a bank has a technological profile similar to fintechs.

Consistent with our findings regarding the geographic diffusion of lending, we find that technology is strongly related to the proportion of out-of-area PPP loans made by a bank. For this paper, we define out-of-area PPP lending as lending in counties or states where a bank does not have a physical, branch presence. We find that the result is driven primarily by the out-of-area lending rather than substitution from in-area lending to out-of-area lending. Technology does not depress in-market PPP loans overall, as might be expected if there were an "either-or" decision to provide local relationship-based lending versus more remote, technological-based loans (or a clear tradeoff between those options). On the other hand, technology is associated with more out-of-area PPP loans, both large and small. We also find that bank technological similarity to fintech lenders on hardware and software are the primary drivers of out-of-area PPP lending conditional on a bank engaging in out-of-area lending.

Following the view that technology enables banks to operate more similarly to fintechs, we examine the extent to which county-level PPP credit supply is met by out-of-area lenders or fintech lenders as a function of local bank technology. We find that those counties whose banks had stronger technological profiles relied less on out-of-county PPP lenders and fintech lenders. In contrast, bank technology does not relate to the proportion of county PPP loans provided by credit unions, consistent with the view that technology is not a primary dimension along which banks competed with credit unions for PPP loans.

Our research is relevant for understanding the impetus of technological innovation in banking and its impact on bank outcomes. Prior innovations include the adoption of Automated Teller Machines (Saloner and Shepard, 1995) and transactional bank websites (DeYoung, Lang, and Nolle, 2007). These innovations and others (i.e. automated clearinghouse) have become widespread and may have contributed to consolidation, though many of the benefits were eventually passed on to consumers (Berger, 2003). Early adoption varied with the characteristics of a bank (e.g. size, extent of branch network, and deposit mix). More recently, Pierri and Timmer (2020) find that banks with higher technology adoption (measured primarily through computers per employee) prior to the 2008 financial crisis subsequently had fewer nonperforming loans. In contrast, our analysis focuses on the role of technology in meeting credit demand when underwriting is a lesser consideration (i.e., backed by the government). In addition, we are the first, to our knowledge, to provide evidence of how a bank's use of technology can be used to mimic fintechs.

Our paper also relates to existing research on the channels through which the banking system, and financial system more generally, responded to the pandemic and associated government programs. Li, Strahan, and Zhang (2020) show that most of the aggregate deposit inflows in 2020Q1 are attributable to credit-line drawdowns at the largest banks. More closely related to this paper, Li and Strahan (2020) find that traditional measures of relationship lending (e.g., decreases in bank size, increases in prior experience, increases in commitment lending, and increases in core deposits) predict PPP lending supply. Erel and Liebersohn (2020) show that fintechs help pick up slack in PPP lending where there exist fewer bank branches and Howell et al. (2021) show that Black-owned businesses were particularly likely to borrow from fintechs. In contrast, we study the role of bank credit supply as a function of technology (while also controlling for some of the balance sheet factors included in previous empirical work). Complementing Li and Strahan (2020), we find that while local relationships mattered for in-area PPP lending, technology is a critical feature to understand the ability of smaller banks to capture shares of PPP lending above and beyond their pre-existing shares of small-business lending.

The rest of the paper is organized as follows. Section II provides some background on the pandemic and the government response. Section III discusses the measures of bank technology used throughout the paper. Section IV examines the relationship between bank technology and PPP lending and compares the PPP lending profile of nonbank fintech lenders to bank PPP lenders. Section V examines the proportion of PPP loans supplied by different segments of the market based on local bank technology. Section VI concludes.

II. Background

The federal government fiscal response in the United States came in the last few weeks of the first quarter of 2020. The first territorial mandatory stay-at-home order was not issued until March 15 (Puerto Rico) and the first state order was not issued until March 19 (California).[9] On March 27, 2020, Congress passed the CARES Act, which included the Paycheck Protection Program (PPP) offering $350 billion in aid to small businesses, later extended to $669 billion

[9]Source: Centers for Disease Control and Prevention.

by the Paycheck Protection Program and Health Care Enhancement Act on April 24, 2020.[10]

Collectively, the government response to the coronavirus is associated with unprecedented increases to the commercial and industrial lending reported on banks' Call Reports. Figure II plots quarterly C&I lending growth from 2000Q2 until 2020Q2. Bank C&I lending grew by $343 billion (15.5 percent) in 2020Q1 and by $146 billion (5.7 percent) in 2020Q2. The first quarter growth is attributable to credit-line drawdowns at the largest banks Li, Strahan, and Zhang (2020). The second quarter includes $482 billion in lending supported by PPP. The distribution of PPP lending across banks was uneven, resulting in substantially greater growth in the highest percentiles of C&I lending (see Figure III).[11] In 2020Q2, the median bank's C&I lending growth increased by over 42 percentage points relative to the median bank's lending growth one year prior: in the prior four years, the increase in the median bank's CI lending growth never exceeded 1 percentage point.

III. Data

Our analysis sample of banks derives from quarterly Call Report data. We consider a set of active banks in 2020Q2 and define balance sheet variables (e.g. assets, or size) from 2019 data. Bank branch locations derive from FDIC Summary of Deposits (SOD) data, reported as of June 30, 2019. We link these data to loan-level data, data on financial technology, and data on location characteristics to assemble our analysis dataset.

A. PPP loan-level data

To analyze the role of technology in PPP lending, we use SBA data on the location and lender names for all PPP loans. To match with Call Report data, we restrict attention

[10]In addition, the CARES Act provided direct stimulus payments of up to $1,200 per adult in households earning less than $99,000 per year. Although the passage of the bill was in the first quarter of 2020, the first stimulus checks were sent April 13, 2020, and the PPP was opened on April 3, 2020.

[11]The Call Reports do not distinguish PPP by loan type. However, Federal Register Vol. 85, No. 98 suggests that most PPP loans were expected to be commercial and industrial lending, with the remainder as agricultural loans and all other loans.

to PPP loans made by June 30, 2020.[12] SBA data does not include a unique institution identifier. Consequently, we match the names of lenders in the PPP data to Call Report names. In addition, we verify matches by cross-referencing the number of loans by institution reported in the Call Reports to the number observed in the SBA data.[13] We use the loan-level PPP data, by institution, to construct several measures of lending described in more detail in Section IV.

B. Local Economic Factors

We include two location-based measures to capture a bank's exposure to the local PPP loan demand and the local economic disruption from the pandemic. Both measures are applied based on the counties in which a bank operates. The PPP loan demand measure is constructed for each bank-county as the total number of competitor PPP loans made in that county divided by the total number of 2019 competitor deposits in that county.

Regarding shocks to labor demand because of COVID, which varied widely across industries, we construct the following economic exposure variable. We first construct a county-level exposure to national industry employment from 2019Q2 to 2020Q2.[14] That is,

$$Exposure_{c,2020Q2} = \sum_i z_{i,c,2019Q2} \cdot g_{i,2019Q2-2020Q2}$$

where industry i represents a three-digit NAICS code, $z_{i,c,2019Q2}$ is the employment share of industry i in county c in 2019Q2, and $g_{i,2019Q2-2020Q2}$ represents the national employment growth for industry i from 2019Q2 to 2020Q2. County-level employment by industry comes from the Quarterly Workforce Indicators (QWI) data from the U.S. Census Bureau.[15]

[12]The program ran until August 2020. As of June 30, 2020, 4.89 million loans were made under PPP. As of August 8, 2020, 5.21 million were made. Source: Treasury PPP Reports, June 30, 2020 and August 8, 2020. The program was reopened on January 11, 2021 and ended May 31, 2021, comprising an additional 6.68 million loans.

[13]Because loans could be withdrawn, the numbers are not expected to match entirely. We drop observations that differ by more than 300% from the PPP data to the Call Report data.

[14]Due to seasonality, especially for harder hit retail and travel industries, this measure is preferred to quarterly employment growth.

[15]This is effectively a Bartik instrument. See Bartik (1992)

Employment growth is sourced from the Bureau of Labor Statistics. Ex-ante exposure to industries that were hard hit by the pandemic strongly predicts subsequent employment outcomes.[16] In unreported results, we regress year-on-year Q2 actual employment growth on predicted employment growth using the industry exposure measure. The coefficient on the predicted unemployment growth measure is approximately 0.5 and the F-statistic is about 40 both with and without state fixed effects and demographic controls. For each bank, we construct the bank-specific labor demand shocks by taking a deposit-weighted average of the county level exposure variable.

C. Fintech Similarity Score

Aberdeen's Product Install table provides information on the vendors and products installed at the establishment level (as defined by Dun & Bradstreet, a business information company) for firms across the United States and Europe. Aberdeen (formerly Harte-Hanks and more recently of Spiceworks Ziff Davis) uses web-mining of businesses and employee profiles for data collection and redistributes it for marketing purposes. The range of products covered includes software, hardware, and communications technologies. While other papers have used Aberdeen data IT expenditures (Pierri and Timmer (2020)), to the best of our understanding this is the first paper to make use of the Product Install tables. The Product Install table is highly granular, with establishment level data on products or models, along with the product class, subclass, and manufacturer.[17] Our analysis focuses on subclasses, which are more granular than classes but more aggregate and more consistently coded than subclass/manufacturer pairings. We find a similar pattern of results whether we examine product installs by class, subclass, or subclass/manufacturer.

To link banks to establishments, we match the Site Description table, which provides a

[16] We exclude counties with less than 10,000 people, as the censoring of small employment values becomes an issue in small counties for calculating county-industry employment shares.

[17] A heirarchical example of hardware product is: Server, Mainframe and data integration (class), Other Server Manufacturer (subclass), IBM (manufacturer), z Mainframe (model). A heirarchical example of software product is: Digital advertising (class), Web Technology (subclass), Google (manufacturer), Google AdWords (model).

location's business name, address and industry information, to the FDIC SOD data on bank branches.[18] Our matching algorithm ultimately covers 95 percent of all banks (i.e. 95 percent of banks have at least one branch that matches to an Aberdeen establishment).

In addition, we identify nonbank fintech firms names from CB Insights 2018, 2020 Forbes 50, American Banker, Medium, and Crunchbase and obtain address information via their websites.[19] This set of fintech firms is composed primarily of lenders. We then use a similar name and address matching method to match the fintech firms with the Aberdeen Site Description to link them to the Product Install table. Aberdeen data include a website address, which we use as an additional matching characteristic. We linked 47 fintech firms to Aberdeen establishment data.

We construct a measure to assess the similarity between banks and fintech firms as:

$$\begin{aligned} FSS &= \textstyle\sum_s^S w_s \max_{p \in P_s} I_p \\ w_s &= \tfrac{1}{F} \textstyle\sum_f^F \max_{p \in P_s} I_p \end{aligned}$$

where Fintech Similarity Score, FSS (or $FinTechScore$ in Tables and Figures), measures bank coverage of fintech technology (i.e. products used by fintechs get more weight). Aberdeen has P products (e.g. Concur Travel - an online booking tool), indexed p, with each product belonging to one of S subclasses (e.g. ERP - Enterprise resource planning - software), indexed s. The indicator I_p equals one for a bank or fintech using product p (and zero otherwise), so $\max_{p \in P_s} I_p = 1$ if the entity uses any of the P_s products in subclass s. There are F fintech firms, indexed f. Subclass weights, w_s, give the share of fintechs with a product in a subclass, a guage of the importance of those products for financial technology.[20] High

[18]Matching is limited to 2019 for both Aberdeen and SOD. Aberdeen establishments are limited to those with a 2-digit SIC code of 60, which includes banks and savings institutions. We standardized names and addresses in both data files. Matching was done in five passes, starting with the key name, street, city, state, zip, and then relaxing some elements of the key. We used a Jaro-Winkler string distance comparator to match name fields.

[19]Examples include Kabbage, a business lender based in Atlanta, GA (see CB Insights 2018) and Plaid, a payments firm based in San Francisco, CA (see 2020 Forbes 50).

[20]Out of forty two product classes, the ten with the greatest weight among fintech firms include four relating to software, four relating to hardware and operating systems, as well as products in customer relationship management and digital advertising.

scores correspond to a bank being more aligned with the technologies that are more prevelant among fintech firms (there is no penalty for having other technologies not present in fintech firms).

D. Summary statistics

Of the 4,092 banks that had the specified characteristic variables for our analysis from Call Reports and local economic factors, we calculate FSS for 3,384 banks that matched to at least one Aberdeen site. Our analysis mostly focuses on the intensive margin of PPP use. In Table I we present summary statistics for the 2,961 of these banks that had at least one PPP loan in 2020Q2. Financial stock variables are measures as the average quarterly balance over 2019, branches are measures as of the June 2019 SOD, financial flow variables are measured as the sum over 2019. Aberdeen data is measured from their 2019 data sample. These tables include log-transformed values for variables entering in regression models in that form.

Figure IV shows the distribution of FSS. As can be seen, there is a heavy right tail to the distribution, with a subset of several hundred banks having substantially greater alignment with fintech technology than the bulk of other banks. We expect that banks in this right tail of the distribution may be especially well positioned to use a wide range of web-based, computational, and remote methods to reach customers during the pandemic. Longitudinal analysis of Aberdeen data from 2017, 2018, and 2019 indicates a similar distribution over time as well as persistence within banks in technology investment. The year-on-year correlation in FSS is 0.792 from 2018 to 2019 and 0.780 from 2017 to 2018. Our analysis will focus on 2019 values of the FSS, though it may be of interest whether banks with longstanding technology investments can be differentiated in their 2020 outcomes relative to banks that are newer to fintech technology.

Because the FSS is highly aggregate, spanning the full range of classes and subclasses, we also conduct some analyses with components of the FSS. We define four components (composed of subclasses): hardware (e.g. PCs, servers), communications (e.g. Virtual Private

Networks, phones), services (e.g. personnel management systems, web hosting, accounting), and software (e.g. digital advertising software, database management software). These components are calculated by first computing the share of all fintech firms in the 2019 Aberdeen data that have at least one install of a subclass. We use these shares as weights of the importance of a subclass for fintech operations within each component. The scores are calculated as the inner product of bank-level subclass indicators with the fintech subclass weights within each component. The software component is substantially broader than the others, comprising more subclasses than all the others combined.

Why do some banks have more extensive technology investment than others in 2019? While this question is not the core focus of our paper, the absence of an answer limits the causal claims we can make in our analysis. Nevertheless, showing how FSS relates to bank characteristics gives some indication of the type of variation that identifies our results. In particular, for our analysis to be meaningful, there must be substantive differences in the technology measures across banks. Here, we show how the technology measures relate to one another as well as to total assets and number of branches. Figure A.VIII displays the relationship of FSS with the log of total assets and the log of number of branches. FSS increases with bank size and number of branches, though there is substantial variabion throughout most of the size distribution. The largest banks possess installs in almost all of the financial technology subclasses, so there is little variation among the largest banks.[21]

IV. Bank PPP Lending

A. Intensive and Extensive Margins of PPP Lending

We first run regressions to examine whether the number of PPP loans issued by a bank are associated with our technology measure and lagged 2019 controls. We examine both the

[21] In Appendix Table A.XIV Column 1, we regress FSS on the bank characteristics used in regression models.

extensive margin of participating in PPP lending and the intensive margin.

$$Pr(PPP > 0) = logit(\beta Tech_b + \Gamma Controls_b) \tag{1}$$

$$Ln(PPPLoans) = \beta Tech_b + \Gamma Controls_b + \epsilon_b \tag{2}$$

We include bank balance sheet variables as controls for traditional factors bank relationship lending (e.g., size, branches, employees, commercial and industrial lending volumes) and also include the two location-based controls for local PPP demand and local economic disruption from the pandemic.

In Table II we report results of the extensive margin and intensive margin regressions of PPP lending on our technology measure, FSS. We first present extensive margin regressions run as a Logit. While we find that FSS has a strong positive relationship with participation in PPP when no controls are included (Column 1), once controls are added there is no significant effect (Column 2). Limiting to banks with at least one PPP loan, we find a strong positive association between the volume of PPP loans and each of the technology measures on the intensive margin (Columns 3, 4, 5, and 6). From the parameter estimate in Column 4, a one standard deviation increase in FSS (from Table I) is associated with a 8.7 p.p. increase in PPP loan volume in 2020Q2. Thus, it appears that technology may be related with the extent of participation in PPP lending, but not the decision to participate. With most banks participating (87.5 percent of our sample), it seems unlikely that technology was a decisive factor for the low threshold of making any PPP loans. Given these results, we focus on the intensive margin and (unless otherwise stated) drop banks that did not participate in PPP.

B. PPP Loan Concentration

If technology enables banks to extend credit by means other than their physical establishments, then we expect that it also results in a more geographically diffuse loan portfolio. The relationship between technology and the concentration of a bank's loan portfolio is particulary salient in the context of government-backed PPP loans where local or soft information is likely to be less valuable for lending decisions.

To examine this hypothesis, we first construct a HHI measure of geographic concentration for banks PPP loans and deposits. In particular, for each bank b we construct:

$$Y\_HHI_b = \sum_g \left(\frac{y_{bg}}{\sum_g y_{bg}} \right)^2$$

where y is the measure of a bank's deposits or loans for geography g.

In Figure V we plot the distribution of banks' county concentrations of deposits (left) and PPP loans (right) for those banks in our regression sample with nonzero PPP lending. Banks with deposits or lending in only one county have an HHI of exactly one. While bank deposits are heavily concentrated in a small number of counties (median HHI of 0.668), bank PPP loans are geographically far more diffuse (0.345).[22] The disparity in the diffusion of banks' PPP loan concentrations relative to their physical deposit presence suggests that factors beyond physical presence must play a role in bank PPP credit supply.

We estimate a regression similar to Equation 2, restricting attention to only those banks with nonzero PPP lending. We report results for the effect of FSS on bank PPP geographic loan concentration in Table III, with Columns 1 through 3 measuring concentration by county and Columns 4 through 6 measuring concentration by state.[23] We include a control of banks' pre-existing geographic concentration, measured primarily with deposits. In Columns 2 and 4 we restrict attention to banks that operate in a single geography, county and state, respectively. That is, for banks in each sample, the deposit HHI is necessarily equal to 1 (so deposit HHI is not included in those specifications).

In each case, and even when restricting to single geography banks, we find that higher values in our technology measure are associated with a less geographically concentrated PPP

[22] Whereas the average banks' deposit base is spread over 1.5 counties, the average banks' PPP loan portfolio is spread across 3 counties. Among Community Reinvestment Act (CRA) lenders, county-concentration is similar for PPP and CRA lending, however, fewer than one in six banks in our sample are CRA lenders and these tend to be substanially larger, consistent with reporting requirements.

[23] See Appendix Table A.XIII for results including controls for loan volume, which do not affect the findings.

loan portfolio. We also find evidence consistent with the established literature on the role of relationship banking. In particular, we find that core deposits and branches are associated with more concentrated PPP lending. Regarding economic significance, a one standard deviation increase in FSS is associated with a decrease in PPP county concentration (from Column 1) of 0.0153 (or 0.0665 standard deviations) and a decrease in state concentration (from Column 4) of 0.0177 (or 0.0804 standard deviations). For perspective, a one standard deviation increase in geographic deposit concentration is associated with an increase in PPP county concentration (from Column 1) of 0.1641 (or 0.713 standard deviations). So, the effects of technology is approximately a tenth as large as the effect of geographic presence.

In Columns 3 and 6 we restrict attention to banks with publicly observable geographic small business lending data for the Community Reinvestment Act (CRA) in 2019.[24] CRA data include loans to businesses with less than \$1 million in revenue and reporting is restricted to banks with greater than \$1.284 billion in total assets as of the end of 2019. Consequently, the sample size is significantly smaller than the sample used in Columns 1 and 4. However, the CRA data allows us to construct a loan concentration measure for banks prior to the pandemic, which we can use as an additional control to understand banks' PPP loan concentrations. In Column 3, we find that banks' PPP county loan concentrations are negatively correlated with FSS even after controlling for banks' CRA loan concentrations. In Column 6, we similarly find that banks' PPP state loan concentrations are negatively correlated with FSS after controlling for CRA state loan concentrations. Notably, the parameter estimates are similar to the estimates in Columns 1 and 4.

C. Fintech Firms versus High-tech Banks

The evidence from prior sections suggests that banks with stronger technology according to our measures issued PPP loans less like branch-centered traditional banks and closer to geography-less fintechs. In this section, we explore the extent to which banks with more technology according to our financial technology measure look like nonbank fintech lenders.

[24] CRA Disclosure Files, Table D1-1.

To do this, we incorporate nonbank data on PPP lending from SBA and rely on the definitions of Erel and Liebersohn (2020) to classify nonbank fintech lenders. Nonbank fintech lenders do not generally have financial data similar to our set of controls for banks. Consequently, we compare banks and nonbank fintechs according to two measures: the quantity of PPP loans and the geographic concentration of PPP loans. Following Erel and Liebersohn (2020), we also restrict attention to those lenders that issued at least 500 PPP loans.

In Figure I, we present kernel density plots of nonbank fintech PPP lending (left panel) and the geographic concentration of PPP lending (right panel), using the county-level construction of HHI as a concentration measure. We segment banks according to FSS (discussed in Section III). In the left plot, we show that the distribution of PPP loan volumes is visually similar between nonbank fintechs and banks with the highest FSS. However, the distribution of PPP loans issued by banks in the 75th to 90th percentile of FSS is notably lower.[25] In the right plot, we show that the distribution of PPP loan HHIs for nonbank fintechs and high-tech banks look fairly similar. In contrast, PPP loan concentration is far higher for those banks in the 75th to 90th percentile of FSS.[26]

By construction, firms with more PPP loans are able to spread their loans across larger geographic areas. As a result, it is helpful to distinguish whether the diffusiveness of PPP loans for nonbank fintech lenders and high-tech banks is a separate issue from the quantity of loans. In Figure VI, for lenders with more than 500 PPP loans, we plot the quantity of loans for nonbank fintech lenders (red), banks in the 75th to 90th percentile in FSS (grey), and banks above the 95th percentile in FSS (blue). For all firms issuing more than 25,000 PPP loans, the geographic concentration of loans is similarly diffuse, i.e. HHI is low. However, for firms issuing fewer loans, we find that only banks with more advanced techonologies have similar diffusion as fintechs. Consistent with theories of banks and fintechs, banks with less

[25] The kernel density plots are skewed even further toward fewer loans for banks in lower percentiles of the FSS distribution.

[26] Despite the visual similarity, a Kolmogorov Smirnov test weakly rejects (90 percent confidence interval) equality between the nonbank FSS distribution and banks with FSS above the 95th percentile for log PPP loans and HHI, respectively. Distributional tests for log PPP loans and HHI between banks in the 70th and 95th percentile and both fintechs and banks in the 95th percentile are strongly rejected (99 percent confidence interval for both).

advanced technology issue loans in more concentrated geographies.

In Table IV we report regression results of loan-county HHI on log PPP loans. To understand how nonbank fintech loan concentration differs from bank lenders we include a nonbank fintech indicator variable. Similar, we include an indicator for banks in the 95th percentile of the FSS distribution. In Columns 1 to 3, we include only those lenders with more than 500 PPP loans. In Columns 4 to 6, we include only lenders with more than 500 PPP loans and less than 25,000 PPP loans. In Columns 2 and 5, we include log PPP loans as a linear terms and in Columns 3 and 6, we allow for a quadratic relationship between log PPP loans and loan HHI. Across all specifications, we find that banks in the 95th percentile FSS and nonbank fintechs are less concentrated in lending geography than other banks. In addition, the concentration difference between banks and nonbank fintechs is cut substantially (a little less than half, for the specifications including a control for lending volume) when a bank is in the 95th percentile in FSS. Thus, it appears that banks with a stronger technology base tend to operate as hybrids between traditional physical branches and fintech lenders.

D. In and Out of Market PPP Lending

Bank lending markets are often physically proximate to their branches, within the county, MSA, or state (see, Federal Deposit Insurance Corporation (2018)). Evidence from Li and Strahan (2020) suggests that physical proximity and measures of traditional banking also played an important role in the participation of banks in the PPP program. In this section, we examine the role that technology played in affecting where banks' lent money under PPP.

While local relationships may have enabled banks to provide PPP loans locally, we hypothesize that technology may have given banks an opportunity to expand the reach of their PPP lending out of area. To understand the role of technology in the location of PPP loans, we run an OLS regression of the proportion of out-of-area PPP loans made by a bank on our technology measures and lagged 2019 controls:

$$\frac{PPP(OutofArea)_b}{PPP(Total)_b} = \beta Tech_b + \Gamma Controls_b + \epsilon_b. \tag{3}$$

We report results from the OLS regression of Equation 3 in Table V. In Columns 1 through 3 we report results of a regression using the proportion of loans made outside of counties with a bank's branch as the dependent variables and in Columns 4 through 6 we report the results of a regression using proportion of loans made outside of states with a bank's branch as the dependent variable. In Columns 1 and 4, we first estimate a Logit with an outcome indicating whether a bank makes any out-of-area loans. For both county and state definitions, technology does not appear to matter on the extensive margin. To investigate the intensive margin, we explain the proportion of out-of-area loans, first for all banks making any PPP loans (in Columns 2 and 5) and then for banks with any out-of-area loans (in Columns 3 and 6). In all of these cases, we find that banks with a higher FSS have a higher percentage of out-of-area loans.

E. Technology Classes

Our results suggest that banks with greater technological investment bear resemblance to fintech firms (as defined in Erel and Liebersohn (2020)) with regard to their ability to lend in areas without a physical branch presence. In this section, we delve further into the kinds of technology installed at banks that are most associated with their PPP lending. We re-run regressions from the above tables using the breakdown of FSS by technology type (hardware, communications, services, and software), as described in Section III and report results in Table VI. We find that the hardware and software components of FSS each have significant, positive effects on loan volume (Columns 2 to 4). For out-of-area lending, the hardware component appears to the strongest effect on dispersed lending and proportion of lending out of area, though software has a similar pattern of estimates, though less precise. The effect of the hardware component is also larger than the software component when measured in terms of a standard deviation change in each component. Thus, it appears that hardware (and its associated technologies, such as server operating systems) plays the most important role in the ability of banks to engage in out-of-area lending, with software playing a secondary role.

F. PPP Lending: Out-of-Area and In-Area Loan Quantities

To unpack the findings of Table V, we examine the quantities of PPP lending in area and out of area. In doing so, we can assess whether banks substitute out-of-area PPP lending for in-area PPP lending or whether they change the total amount of PPP loans. We run regressions of the following form by loan size and in- or out-of-area markets:

$$Ln(PPP + 1)_b = \beta Tech_b + \Gamma Controls_b + \epsilon_b. \tag{4}$$

We define in-area as those regions (i.e., county or state, depending on the specification) where a bank had a physical branch as of June 2019 and out-of-area as those regions where the bank did not have a physical branch.

In Table VII, we report the results from the regression of out-of-area PPP loans on the FSS measure and controls. In Columns 1 through 3 we report results for out-of-county PPP loans and in Columns 4 through 6 we report results for out-of-state PPP lending. In Column 1, we find that the FSS is strongly correlated with the number of out-of-county PPP loans. We find that the effect is similar for small (<\$1 million) PPP loans in Column 2 and large (>\$1 million) PPP loans in Column 3. We find similar results for out-of-state PPP lending.

Though we find that the increase in the proportion of out-of-area lending is driven in part by more out-of-area PPP loans, we also examine whether the technology is associated with decreases in in-area PPP lending. That is, does technology depress the relationship lending function found in Li, Strahan, and Zhang (2020)?

To examine in-area lending quantities, we run regressions of in-area lending at the bank and bank-geography levels. As above, geographies are defined at the county and state levels.[27]

[27]Note that we cannot perform similar analysis for out-of-area bank-geographies, as we do not have any similar

We report the results from the in-area regressions of lending in Table VIII.

In Column 1, we report results of a bank-level regression of in-county PPP loans on the FSS and bank controls. We do not find a significant relationship between technology and in-area PPP lending. We then examine the data at the bank-geography level, allowing for geography fixed effects as well as bank-geography specific measures on local presence, such as number of branches or deposits. Given the ability to control for local factors using fixed effects, we also exclude the bank-level local economy proxies of local PPP loan demand and exposure to COVID related employment shocks. The results do not differ materially when including them in lieu of geography fixed effects.

In Columns 2 through 4 we report results using the number of in-county PPP loans including bank-county fixed effects. In Column 2 we find that banks with a higher FSS did not make any more or less PPP loans in counties where they had a physical presences, relative to other banks. We find that technology has a slight negative relationship in Column 3 with the number of small (<$1 million) PPP loans. However, we find in Column 4 that banks with a higher FSS were associated with more large (>$1 million) in-county PPP loans. Consistent with Li and Strahan (2020), we find that local presence, measured using in-county deposits and/or branches, is associated with in-county PPP loans, for both small and large loans.

In Columns 5 through 8 we report results of similar regressions at the bank-state level. In Column 5, we do not find that a higher FSS is associated with more in-state PPP lending at the bank-level and similarly in Column 6 we find no association with PPP lending at the bank-state level, after controlling for state fixed effects. Similar to the bank-county analysis, in Columns 7 and 8 we find that there is no relationship between small PPP in-state loans and technology, but there is a a strong positive association between technology and large in-state PPP loans. Furthermore, we find that in-state measures of physical presence (deposits and branches) are significant drivers of in-state PPP lending for all loan sizes. Combined with the results from Section IV.F, the results suggest that the relationship between technology and

measure of a bank's presence in a geography out-of-area prior to the pandemic. Furthermore, there is not a clear way to establish the appropriate set of bank-geographies for out-of-area lending, as the vast majority of bank-geography pairs are associated with zero PPP loans.

the proportion of PPP loan out-of-area is driven primarily by increases in out-of-area loans and not through the substitution of in-area loans for out-of-area loans.

G. Expense-based measures of financial technology

As alternative measures of bank use of financial technology, we consider two expense-based measures reported by banks in quarterly Call Reports. We expect that these measure may capture different aspects of technology than our product-based measure, FSS, though they may also affect lending outcomes. Whereas we expect that FSS most directly reflects the types in-house technological capabilities of a bank, our expense measures may reflect both the scale of technology investment and use of external, contracted capabilities (and potentially partnerships).

Our first alternative measure, other noninterest expenses (Call Report Schedule RI, item 7.d.) reports spending other than salaries and employee benefits, premises and fixed assets, and intangible assets. As reported below, we find that the plurality of other noninterest expenses are associated with data processing. Additional subitems that may relate to technology include advertising and marketing expenses and telecom expenses. Other noninterest expense also includes research and development costs incurred in the internal development of computer software. Our second alternative measure, data processing expeneses (Call Report Schedule RI-E, item 2.a.) is more specific to technology, and reports "services performed for the bank by others."

From Call Reports, we observe other noninterest expense for all banks, but subitems, including data processing, may be censored. As of 2018, subitems of other noninterest expense have minimum reporting thresholds of $100,000 and seven percent of other noninterest expenses. The data does not distinguish between true zeros and censored values, and some banks below the reporting thresholds respond anyways. In addition, due to year-to-date (cumulative) reporting on quarterly filings, there are substantially more censored observations for earlier quarters. For our analysis, we use the most recent year-end values of other noninterest expense and noncensored values of data processing expense. From 2016 to 2019, there is a noncensored observation for bank data processing expenses for 81 percent of banks' December Call Report data.[28]

Other noninterest expense is best understood by examining its components. Table IX reports statistics on the breakdown of subitems in Schedule RI-E relative to other noninterest expense. We also report the count of nonzero observations, and note the exact shares of each subitem are not certain (and could be higher or lower) due to censoring across each of the subitems. Data processing expenses account for the plurality of other noninterest expenses, but still represent just 19.1 percent of other noninterest expense on average (treating empties as zero). If we restrict to only those observations with strictly positive data processing expenses, it makes up approximately 24 percent of other noninterest expenses. The next largest (observed) driver of other noninterest expense in Schedule RI-E is advertising and marketing expenses, which accounts for 5.0 percent of other noninterest expense and may include expenses on digital advertising. Telecommunications expenses associated with telephone, telegraph, cable, and internet services (including web page maintenance) account for 2.6 percent of observed total other noninterest expenses. Thus, the plurality of expenses captured by other noninterest expense reflects the technology investments of interest, though the measure incorporates many other expenses outside our scope of interest.

Figure VII displays the relationship of FSS with other noninterest expense and data processing expense. While one might expect these measures to be related (as larger banks might use more technology), the product information clearly presents another dimension of technology investment. These figures show that the expense and product install measures capture related, but somewhat different dimensions of technology investment and exhibit variation across a wide range of bank sizes.[29]

[28]In unreported analysis, we use multiple imputations for data processing expenses. Because the censored variable is necessarily selected on the basis of the censored variable's value, the multiple imputation uses only those banks below the reporting thresholds that nevertheless report data processing expenses. All results using data processing expenses are robust to using multiply imputed data rather than restricting to uncensored values.

[29]Appendix Table A.XIV Columns 2 and 3, explains other noninterest expense and data processing expense in terms of the main specification control variables.

Table X reports results equivalent to Table II (for PPP lending and volume) and III (for geographic concentration of lending). These expense results exhibit a similar pattern as the FSS results using Aberdeen data for product installs as a measure of technology. Table XI presents additional results that include both FSS and expense based measures. The effect of FSS on loan volume remains positive and statistically significant, and the effect of FSS on loan concentration remains negative and significant, even when including expense-based measures of technology alongside FSS. These results suggest that product- and expense-based investments in financial technology may have similar, complementary effects that facilitate processing of PPP loans, especially for out-of-area borrowers.

V. County PPP Loan Supply

Our bank-level results suggest that technology heavy banks operate more similarly to fintechs than other banks. Consequently, we expect that a borrower inclined to use a technologically-based lender is more likely to view local bank technology as a substitute for a potentially out-of-area loan. Even so, that tendancy may be diminished if local banks are more technologically savvy.

Thus, we examine whether the local presence of technology heavy banks relates to the nature of competition for local PPP loans. In particular, we expect that a county with more technologically-oriented banks might rely less on out-of-area lenders in general, or fintechs in particular, than counties with less technologically-oriented banks. On the other hand, we expect that technology plays a lesser role in local banks' abilities to compete for customers more associated with traditional relationship lending.

To examine these hypotheses, we construct a county-level bank technology variable equal to the deposit-weighted average of banks' FSS for that county. Similarly, we construct a measure of the deposit-weighted average of log bank assets. We also include county aggregates of bank branches, credit union branches, and the county-level deposit HHI (where county-shares are calculated at the bank level). We also incorporate demographic data such as the county population, percentage of the population in urban areas, percentage of the population aged 65 or older, and the year-on-year 2020Q2 employment growth.

For each county, we calculate the percentage of PPP loans made from out-of-county lenders, the percentage of loans made by fintechs (previously defined), the percentage of PPP loans made out-of-area by technologically savvy small banks (defined as top 95th percentile FSS and less than $10 billion in assets), and the percentage of PPP loans made by credit unions. In calculating out-of-county loans, we classify all fintech loans as out-of-area.

In Table XII we report the results of county-level OLS regressions of the relative proportion of county lending filled by different loan supply. In Columns (1) and (2) we find that local bank technology is negatively correlated with the proportion of loans made from out-of-area lenders. Thus, counties with more technologically savvy local banks relied proportionally less on out-of-area banks to meet their PPP credit demand. Similarly, in Columns (3) and (4) we find that local bank technology is also negatively related to the reliance of a county on using fintech firms to meet local PPP credit demand. In Columns (5) and (6), we examine the extent to which the PPP credit is supplied by out-of-area technologically savvy small banks–those in the 95th percentile FSS and less than $10 billion in assets as discussed in Section IV.C, finding weak evidence that local bank technology substitutes for out-of-area bank PPP lending. In contrast, in Columns (7) and (8) we find that local bank technology does not relate to the proportion of PPP credit supplied by credit unions, consistent with the view that technology is not a primary determinant driving a borrower's decision to chose a bank relative to a credit union for a PPP loan. Thus, the county-level results suggest that local bank adoption of technology may reduce reliance on out-of-area, technologically savvy lenders to fulfill local credit needs.

VI. Conclusion

How did small banks succeed in the transaction-based, information insensitive PPP loan market? This paper examines lending outcomes for the banking industry, early in the pandemic, that demonstrate the immediate utility of pre-existing investments in technology. We examine how technology helped direct borrowers to lenders through the federal government's PPP business lending program, which occurred in the second quarter of 2020. We use a detailed record of product installations, prior to the pandemic, across a range of technologies (hardware, communications, services, and software) and calculate how closely a bank's technology profile aligns with nonbank fintech firms.

We find that these investments in technology enhanced banks' reach of borrowers, both large and small, and especially to borrowers outside of their branch network. This expanded reach does not appear to come at the expense of lending to more proximate borrowers. Hardware investments, in particular, appear to be the most consequential for increased lending out of area, with software playing a secondary role. Our estimation procedures control for a wide range of bank characteristics and local economic shocks and include fixed effects where possible. We find similar results using expense data from quarterly financial statements as a measure of financial technology. The product- and expense-based measures appear to capture different aspects of technology, as both have a similar pattern of results on their own, but the point estimates of the product-based measure are relatively stable when the expense-based measures are added to empirical models. We further find that counties with more technologically savvy banks had less borrowing from nonbank fintechs and high-technology out-of-area banks. Collectively, the evidence suggests that technology-oriented banks operate as a hybrid between fintech firms and traditional banks with their ability to lend out-of-area while retaining a local lending capacity.

Future work might further tease out the causal effects of technology. One concern may be that banks with substantial investments in technology may be better positioned or have more apt or forward looking managers. Such banks might be expected to respond well to the tumultuous circumstances of the pandemic, so perhaps it is not technology, but other characteristics of banks that are most essential to deposit and lending outcomes. We have attempted to address this concern using a large set of controls and a variety of specifications. Future research might examine whether banks can quickly catch up to the industry leaders, in terms of technology, or whether differences are persistent. Although we do not claim causal identification, our results demonstrate an important relationship between pre-existing technology investments and outcomes in the banking industry during the COVID-19 pandemic.

REFERENCES

Bartik, Timothy J., 1992, The Effects of State and Local Taxes on Economic Development: A Review of Recent Research, *Economic Development Quarterly* 6, 102–111.

Berger, Allen N., 2003, The Economic Effects of Technological Progress: Evidence from the Banking Industry, *Journal of Money, Credit and Banking* 35, 141–176.

Bolton, Patrick, Xavier Freixas Freixas, Leonardo Gambacorta, and Paolo Emilio Mistrulli, 2016, Relationship and Transaction Lending in a Crisis, *The Review of Financial Studies* 29, 2643–2676.

Cortés, Kristle R., Yuliya Demyanyk, Lei Li, Elena Loutskina, and Philip E. Strahan, 2020, Stress tests and small business lending, *Journal of Financial Economics* 136, 260–270.

DeYoung, Robert, William W. Lang, and Daniel L. Nolle, 2007, How the Internet affects output and performance at community banks, *Journal of Banking & Finance* 31, 1033–1060.

Erel, Isil, and Jack Liebersohn, 2020, Does FinTech Substitute for Banks? Evidence from the Paycheck Protection Program, *National Bureau of Economic Research* No. w27659.

Federal Deposit Insurance Corporation, 2018, FDIC Small Business Lending Survey.

Howell, Sabrina T, Theresa Kuchler, David Snitkof, Johannes Stroebel, and Jun Wong, 2021, Racial Disparities in Access to Small Business Credit: Evidence from the Paycheck Protection Program, *National Bureau of Economic Research Working Paper Series* No. 29364.

Li, Lei, and Philip E. Strahan, 2020, Who Supplies PPP Loans (And Does It Matter)? Banks, Relationships and the COVID Crisis, Available at SSRN 3710929.

Li, Lei, Philip E. Strahan, and Song Zhang, 2020, Banks as Lenders of First Resort: Evidence from the COVID-19 Crisis, *The Review of Corporate Finance Studies* 9.

Pierri, Nicola, and Yannick Timmer, 2020, Tech in Fin before FinTech: Blessing or Curse for Financial Stability?, *IMF Working Paper* 20/14.

Saloner, Garth, and Andrea Shepard, 1995, Adoption of Technologies with Network Effects: An Empirical Examination of the Adoption of Automated Teller Machines, *The RAND Journal of Economics* 26, 479–501.

Thakor, Anjan V., 2020, Fintech and Banking: What Do We Know?, *Journal of Financial Intermediation* 41.

Vives, Xavier, 2019, Digital Disruption in Banking, *Annual Review of Financial Economics* 11, 243–272.

Table I: Summary statistics for PPP estimation models. Sample observations have more than one PPP loans as well as nonmissing values of bank controls and FSS. Financial stock variables are measures as the average quarterly balance over 2019, branches are measures as of the June 2019 SOD, financial flow variables are measured as the sum over 2019. Aberdeen data is measured from their 2019 data sample. Untransformed dollar values are reported in millions.

	mean	p50	sd	count
PPP loans	1303	219	10096	2961
PPP loans Out of County	341	44	3976	2961
PPP loans Out of State	243	6	3868	2961
PPP loans In County	962	149	9062	2961
PPP loans In State	1060	192	9235	2961
Percent PPP Out of County	0.27	0.21	0.22	2961
Percent PPP Out of State	0.09	0.03	0.18	2961
countyhhi_ppp	0.38	0.35	0.23	2961
statehhi_ppp	0.82	0.93	0.22	2961
CountyHHI_Dep	0.67	0.67	0.30	2961
StateHHI_Dep	0.95	1.00	0.15	2961
CountyCRA_HHI	0.23	0.18	0.21	447
StateCRA_HHI	0.71	0.81	0.28	447
FSS	16.44	14.11	8.93	2961
FSS_Comm	0.70	0.74	0.32	2961
FSS_Hard	2.09	2.02	0.93	2961
FSS_Serv	0.09	0.00	0.29	2961
FSS_Soft	13.54	11.70	7.80	2961
OthNonIntX_{t-2}	42.08	2.33	658.67	2960
DataProc_{t-2}	6.40	0.55	115.54	2481
Emp_{t-2}	564	57	7148	2961
CoreDep_{t-2}	3031	216	41502	2961
Eq_{t-2}	544	32	7364	2961
CI_{t-2}	636	19	8362	2961
Branch_{t-2}	24	5	190	2961
Commitment_{t-2}	1970	30	34504	2961
Asset_{t-2}	4835	284	69516	2961
COVID_Exposure	-0.1432	-0.1432	0.0310	2961
PPP_Demand	0.0812	0.0764	0.0390	2961
Ln(PPP Loan)	5.45	5.39	1.53	2961
Ln(Out of County PPP Loan)	3.90	3.81	1.59	2961
Ln(Out of State PPP Loan)	2.30	1.95	1.91	2961
Ln(In County PPP Loan)	5.02	5.01	1.59	2961
Ln(In State PPP Loan)	1.27	0.69	1.42	2961
$\text{Ln}(\text{OthNonIntX}_{t-2})$	7.96	7.76	1.46	2959
$\text{Ln}(\text{DataProc}_{t-2})$	6.46	6.31	1.35	2481
$\text{Ln}(\text{Emp}_{t-2})$	4.21	4.03	1.36	2961
$\text{Ln}(\text{CoreDep}_{t-2})$	12.48	12.28	1.44	2961
$\text{Ln}(\text{Eq}_{t-2})$	10.59	10.38	1.48	2961
$\text{Ln}(\text{CI}_{t-2})$	10.04	9.88	1.87	2961
$\text{Ln}(\text{Branch}_{t-2})$	1.67	1.61	1.21	2961
$\text{Ln}(\text{Commitment}_{t-2})$	10.47	10.31	1.89	2961
$\text{Ln}(\text{Asset}_{t-2})$	12.76	12.56	1.47	2961

Table II: Logistic regressions on participation of PPP lending (extensive margin) and number of PPP loans conditional on participation (intensive margin). Columns 1 and 2 report logistic regression results where the outcome variable is equal to 1 if a bank issues any PPP loans and zero otherwise. Columns 3 through 6 report regression results of log PPP loans on FSS and other bank controls conditional on banks' participation in PPP.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Pr(PPP>0)	Pr(PPP>0)	Ln(Loan)	Ln(Loan)	Ln(Loan<1m)	Ln(Loan≥1m)
FSS	0.0570***	-0.0123	0.101***	0.00975***	0.00880***	0.0198***
	(0.00887)	(0.00998)	(0.00313)	(0.00270)	(0.00258)	(0.00271)
Ln(Emp_{t-2})		0.194		0.409***	0.389***	-0.0441
		(0.210)		(0.0824)	(0.0815)	(0.0653)
Ln(CoreDep_{t-2})		1.295***		0.105	0.141	0.271
		(0.445)		(0.249)	(0.248)	(0.180)
Ln(Eq_{t-2})		0.0230		-0.288***	-0.245***	0.158**
		(0.239)		(0.0821)	(0.0756)	(0.0738)
Ln(CI_{t-2})		0.278***		0.242***	0.209***	0.289***
		(0.0517)		(0.0232)	(0.0210)	(0.0231)
Ln(Branch_{t-2})		0.510***		0.00813	0.0696	-0.0575
		(0.147)		(0.0534)	(0.0524)	(0.0398)
Ln(Commitment_{t-2})		0.551***		0.245***	0.254***	0.173***
		(0.0773)		(0.0377)	(0.0359)	(0.0333)
Ln(Asset_{t-2})		-2.156***		0.0259	-0.0603	-0.144
		(0.567)		(0.255)	(0.252)	(0.197)
PPP_Demand		-1.517		1.616***	-0.348	-2.027***
		(1.266)		(0.461)	(0.391)	(0.383)
COVID_Exposure		0.764		-1.801***	-1.825***	-0.577
		(1.691)		(0.514)	(0.464)	(0.529)
Constant	1.116***	3.817**	3.786***	-0.413	0.256	-6.483***
	(0.129)	(1.758)	(0.0519)	(0.576)	(0.567)	(0.494)
Observations	3,384	3,384	2,961	2,961	2,961	2,961
R-squared			0.349	0.676	0.708	0.702

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table III: Regressions of the geographic concentration of bank PPP loans on FSS and bank controls. Columns 1 through 3 use a measure of HHI based on bank-level county shares of PPP lending. Columns 4 through 6 use a measure of HHI based on bank-level state shares. The samples in Columns 1 and 4 include all banks with nonzero PPP lending for which other controls are observable. Columns 2 and 5 subset to those banks that with branches in a single geographic area, county and state, respectively. Columns 3 and 6 subset to those banks with county-level Community Reinvestment Act data in 2019.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	County HHI	County HHI	County HHI	State HHI	State HHI	State HHI
FSS	-0.00172***	-0.00425***	-0.00147**	-0.00198***	-0.00257***	-0.00258***
	(0.000421)	(0.00145)	(0.000629)	(0.000536)	(0.000645)	(0.000930)
Ln(Emp_{t-2})	-0.0375***	-0.0569**	-0.0363**	-0.0548***	-0.0470***	-0.0281
	(0.0111)	(0.0231)	(0.0152)	(0.0138)	(0.0156)	(0.0203)
Ln(CoreDep_{t-2})	0.214***	0.273***	0.0972***	0.209***	0.203***	0.0980
	(0.0220)	(0.0432)	(0.0375)	(0.0314)	(0.0339)	(0.0692)
Ln(Eq_{t-2})	0.0149	0.0103	0.00370	0.0268*	0.0212	0.00962
	(0.0147)	(0.0289)	(0.0245)	(0.0154)	(0.0165)	(0.0364)
Ln(CI_{t-2})	-0.0201***	-0.0359***	-0.0115	-0.0196***	-0.0193***	-0.0119
	(0.00428)	(0.00778)	(0.00816)	(0.00459)	(0.00500)	(0.0124)
Ln(Branch_{t-2})	0.0517***	0.0825***	0.0230*	0.0448***	0.0484***	0.0251*
	(0.00878)	(0.0165)	(0.0118)	(0.00959)	(0.0108)	(0.0152)
Ln(Commitment_{t-2})	-0.00411	0.00491	0.00760	-0.00256	0.00119	-0.00970
	(0.00662)	(0.0116)	(0.0100)	(0.00732)	(0.00796)	(0.0155)
Ln(Asset_{t-2})	-0.200***	-0.234***	-0.0730	-0.192***	-0.190***	-0.0583
	(0.0301)	(0.0614)	(0.0463)	(0.0372)	(0.0406)	(0.0723)
PPP_Demand	0.301***	0.333	0.773***	0.357***	0.290***	0.728**
	(0.0983)	(0.205)	(0.186)	(0.0993)	(0.106)	(0.319)
COVID_Exposure	-0.537***	-0.509**	0.0329	-0.124	-0.0808	-0.155
	(0.103)	(0.215)	(0.194)	(0.104)	(0.119)	(0.197)
CountyHHI_Dep	0.547***		0.266***			
	(0.0136)		(0.0396)			
CountyCRA_HHI			0.545***			
			(0.0581)			
StateHHI_Dep				0.876***		0.394***
				(0.0226)		(0.0553)
StateCRA_HHI						0.537***
						(0.0512)
Constant	-0.0176	0.428**	-0.195	-0.0843	0.852***	-0.343
	(0.0917)	(0.185)	(0.137)	(0.105)	(0.113)	(0.232)
Observations	2,961	966	445	2,961	2,458	445
R-squared	0.531	0.140	0.803	0.422	0.075	0.765

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table IV: Regressions of lender-level geographic PPP loan concentration using county shares. Fintech is an indicator variable equal to 1 for firms identified in Erel and Liebersohn (2020) and zero otherwise. Bank95th are banks with FSS at or above the 95th percentile. Columns 1 through 3 include all bank and fintech lenders with at least 500 PPP loans. Columns 4 through 6 include bank and fintech lenders with PPP loans between 500 and 25,000 loans.

VARIABLES	(1) Loan HHI	(2) Loan HHI	(3) Loan HHI	(4) Loan HHI	(5) Loan HHI	(6) Loan HHI
Bank95th	-0.145***	-0.0597***	-0.0604***	-0.137***	-0.0575***	-0.0659***
	(0.0117)	(0.0129)	(0.0128)	(0.0124)	(0.0137)	(0.0133)
Fintech	-0.175***	-0.127***	-0.129***	-0.173***	-0.131***	-0.137***
	(0.0127)	(0.0125)	(0.0112)	(0.0129)	(0.0122)	(0.0111)
Ln(PPPLoans)		-0.0605***	-0.248***		-0.0712***	-0.333***
		(0.00477)	(0.0379)		(0.00605)	(0.0819)
$(\text{Ln(PPPLoans)})^2$			0.0115***			0.0171***
			(0.00211)			(0.00514)
Constant	0.247***	0.673***	1.421***	0.248***	0.748***	1.733***
	(0.00673)	(0.0358)	(0.163)	(0.00674)	(0.0445)	(0.321)
Observations	934	934	934	913	913	913
R-squared	0.098	0.187	0.200	0.085	0.173	0.180

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table V: Regressions of out-of-area PPP loans on FSS and controls. Columns 1 through 3 define out-of-area as counties in which a bank does not have a branch location. Columns 4 through 6 define out-of-area as states in which a bank does not have a branch locations. Columns 1 and 4 report results of logistic regression, where the outcome variable is a binary variable equal to one if the bank recorded any out-of-area lending and zero otherwise. Columns 2 and 5 report the results of an OLS regression of the proportion of out-of-area PPP loans to total PPP loans including all banks in the sample that made PPP loans. Columns 3 and 6 report the results of an OLS regression of the proportion of out-of-area PPP loans to total PPP loans for those banks with nonzero out-of-area PPP loans.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Pr(Out County)	Out County Pct	Out County Pct > 0	Pr(Out State)	Out State Pct	Out State Pct > 0
FSS	-0.0195	0.00288***	0.00301***	0.00511	0.00266***	0.00324***
	(0.0295)	(0.000609)	(0.000611)	(0.0107)	(0.000563)	(0.000633)
Ln(Emp_{t-2})	-0.0104	0.0314**	0.0319**	0.219	0.0422***	0.0385**
	(0.852)	(0.0150)	(0.0150)	(0.216)	(0.0155)	(0.0178)
Ln($CoreDep_{t-2}$)	-0.808	-0.232***	-0.230***	-1.040*	-0.190***	-0.192***
	(1.588)	(0.0317)	(0.0316)	(0.537)	(0.0376)	(0.0407)
Ln(Eq_{t-2})	0.201	0.00495	0.00591	-0.496**	-0.0126	0.00854
	(0.775)	(0.0191)	(0.0191)	(0.244)	(0.0158)	(0.0194)
Ln(CI_{t-2})	0.498***	0.0180***	0.0157***	0.472***	0.0132***	0.00878
	(0.115)	(0.00515)	(0.00533)	(0.0628)	(0.00453)	(0.00612)
Ln($Branch_{t-2}$)	0.178	-0.0700***	-0.0714***	0.105	-0.0425***	-0.0458***
	(0.677)	(0.0106)	(0.0107)	(0.132)	(0.0102)	(0.0119)
Ln($Commitment_{t-2}$)	0.798***	0.00199	-0.00291	0.290***	-0.00285	-0.0131
	(0.267)	(0.00828)	(0.00839)	(0.0933)	(0.00809)	(0.0102)
Ln($Asset_{t-2}$)	0.0219	0.183***	0.187***	1.499**	0.166***	0.157***
	(2.034)	(0.0394)	(0.0392)	(0.670)	(0.0423)	(0.0461)
PPP_Demand	-4.078	-0.579***	-0.559***	0.955	-0.234**	-0.286**
	(3.010)	(0.123)	(0.122)	(1.348)	(0.106)	(0.122)
COVID_Exposure	-0.960	0.415***	0.427***	-1.714	0.102	0.189*
	(4.211)	(0.137)	(0.137)	(1.831)	(0.0938)	(0.109)
Constant	0.238	0.626***	0.618***	-7.889***	0.248**	0.379***
	(6.670)	(0.116)	(0.115)	(1.635)	(0.107)	(0.124)
Observations	2,961	2,961	2,928	2,961	2,961	2,453
R-squared		0.113	0.118		0.051	0.064

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table VI: Regressions of bank-level PPP outcomes on FSS component scores and controls. Column 1 reports results from a logistic regression of PPP participation on FSS components and controls. Column 2 reports results from an OLS regression of log PPP loans on FSS components and controls for those banks with nonzero PPP loans. Columns 3 and 4 reports results from an OLS regression of log PPP loans less than \$1 million and greater than \$1 million, respectively, on FSS components and controls for those banks with nonzero PPP loans. Column 5 reports results from an OLS regression of bank-level geographic PPP loan concentration on FSS components and controls for those banks with nonzero PPP loans. Columns 6 and 7 report results of OLS regression of out-of-county PPP loans to total PPP loans, for all PPP lending banks and those with nonzero out-of-county lending, respectively, on FSS components and controls for those banks with nonzero PPP loans.

VARIABLES	(1) Pr(PPP>0)	(2) Ln(Loan)	(3) Ln(Loan<1m)	(4) Ln(Loan≥1m)	(5) County HHI	(6) OutCtyPctAll	(7) OutCtyPctPos
FSS_Comm	-0.0392	0.0107	-0.0228	-0.0593	0.00725	-0.00900	-0.0100
	(0.206)	(0.0588)	(0.0547)	(0.0592)	(0.0124)	(0.0156)	(0.0157)
FSS_Hard	-0.252**	0.0686**	0.0847***	0.0900***	-0.0170***	0.0298***	0.0329***
	(0.111)	(0.0315)	(0.0295)	(0.0300)	(0.00580)	(0.00747)	(0.00746)
FSS_Serv	-0.653*	-0.237***	-0.270***	-0.0651	0.0282**	-0.0441**	-0.0426**
	(0.375)	(0.0824)	(0.0783)	(0.0843)	(0.0120)	(0.0203)	(0.0203)
FSS_Soft	0.0241	0.0109**	0.00995***	0.0173***	-0.00131*	0.00189*	0.00172*
	(0.0150)	(0.00424)	(0.00384)	(0.00398)	(0.000732)	(0.000980)	(0.000982)
$Ln(Emp_{t-2})$	0.171	0.405***	0.385***	-0.0407	-0.0380***	0.0323**	0.0331**
	(0.205)	(0.0822)	(0.0812)	(0.0655)	(0.0111)	(0.0150)	(0.0151)
$Ln(CoreDep_{t-2})$	1.302***	0.102	0.136	0.265	0.215***	-0.234***	-0.232***
	(0.422)	(0.248)	(0.247)	(0.181)	(0.0219)	(0.0315)	(0.0315)
$Ln(Eq_{t-2})$	0.0240	-0.279***	-0.235***	0.156**	0.0146	0.00505	0.00547
	(0.237)	(0.0829)	(0.0762)	(0.0743)	(0.0148)	(0.0192)	(0.0192)
$Ln(CI_{t-2})$	0.279***	0.242***	0.209***	0.290***	-0.0203***	0.0182***	0.0158***
	(0.0511)	(0.0232)	(0.0209)	(0.0230)	(0.00429)	(0.00516)	(0.00533)
$Ln(Branch_{t-2})$	0.528***	0.00665	0.0677	-0.0624	0.0517***	-0.0721***	-0.0739***
	(0.138)	(0.0536)	(0.0526)	(0.0401)	(0.00884)	(0.0107)	(0.0107)
$Ln(Commitment_{t-2})$	0.542***	0.242***	0.250***	0.173***	-0.00401	0.00194	-0.00288
	(0.0770)	(0.0378)	(0.0360)	(0.0333)	(0.00662)	(0.00827)	(0.00836)
$Ln(Asset_{t-2})$	-2.155***	0.0270	-0.0578	-0.138	-0.201***	0.185***	0.190***
	(0.546)	(0.254)	(0.251)	(0.198)	(0.0301)	(0.0394)	(0.0392)
PPP_Demand	-1.533	1.611***	-0.356	-2.038***	0.301***	-0.582***	-0.563***
	(1.281)	(0.463)	(0.392)	(0.384)	(0.0985)	(0.124)	(0.123)
CountyHHI_Dep					0.542***		
					(0.0139)		
COVID_Exposure	1.037	-1.812***	-1.842***	-0.623	-0.532***	0.396***	0.404***
	(1.667)	(0.512)	(0.460)	(0.532)	(0.104)	(0.137)	(0.137)
Constant	4.008**	-0.562	0.0956	-6.542***	0.00510	0.587***	0.576***
	(1.738)	(0.580)	(0.570)	(0.500)	(0.0924)	(0.116)	(0.115)
Observations	3,384	2,961	2,961	2,961	2,961	2,961	2,928
R-squared		0.677	0.709	0.702	0.533	0.118	0.123

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table VII: Regressions of the out-of-area PPP loans on FSS and controls. Columns 1 through 3 estimate the relationship between out-of-county PPP loans and the regressors on the intensive margin (no banks in the sample have no out-of-county loans). Columns 4 through 6 estimate the relationship between out-of-state PPP loans and the regressors on the intensive margin (no banks in the sample have no out-of-county loans).

	PPP Out of County			PPP Out of State		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Ln(Loan)	Ln(Loan<1m)	Ln(Loan≥1m)	Ln(Loan)	Ln(Loan<1m)	Ln(Loan≥1m)
FSS	0.0186***	0.0186***	0.0211***	0.0269***	0.0273***	0.0176***
	(0.00376)	(0.00381)	(0.00281)	(0.00516)	(0.00521)	(0.00312)
Ln(Emp$_{t-2}$)	0.463***	0.465***	-0.00651	0.477***	0.489***	0.0901
	(0.0993)	(0.101)	(0.0666)	(0.134)	(0.135)	(0.0755)
Ln(CoreDep$_{t-2}$)	-0.633**	-0.637**	-0.152	-1.126***	-1.120***	-0.352**
	(0.261)	(0.266)	(0.158)	(0.333)	(0.340)	(0.171)
Ln(Eq$_{t-2}$)	-0.282***	-0.293***	0.216***	-0.0289	-0.0404	0.309***
	(0.104)	(0.105)	(0.0699)	(0.145)	(0.146)	(0.0794)
Ln(CI$_{t-2}$)	0.316***	0.307***	0.270***	0.328***	0.316***	0.216***
	(0.0294)	(0.0295)	(0.0209)	(0.0429)	(0.0430)	(0.0244)
Ln(Branch$_{t-2}$)	-0.240***	-0.228***	-0.139***	-0.217**	-0.219**	-0.152***
	(0.0617)	(0.0631)	(0.0436)	(0.0868)	(0.0885)	(0.0525)
Ln(Commitment$_{t-2}$)	0.190***	0.192***	0.0608*	0.0730	0.0649	-0.0101
	(0.0474)	(0.0478)	(0.0319)	(0.0686)	(0.0693)	(0.0371)
Ln(Asset$_{t-2}$)	0.635**	0.641**	0.0735	0.845**	0.855**	0.123
	(0.285)	(0.293)	(0.178)	(0.366)	(0.374)	(0.187)
PPP_Demand	-0.292	-0.750	-1.600***	-1.323	-1.254	-1.030***
	(0.570)	(0.587)	(0.373)	(0.856)	(0.864)	(0.390)
COVID_Exposure	1.140*	1.189*	-0.0568	-0.418	-0.340	0.593
	(0.687)	(0.690)	(0.513)	(0.928)	(0.928)	(0.560)
Constant	-0.110	0.0897	-3.871***	0.108	0.170	-2.309***
	(0.690)	(0.703)	(0.498)	(0.932)	(0.945)	(0.558)
Observations	2,928	2,928	2,928	2,453	2,453	2,453
R-squared	0.431	0.424	0.481	0.265	0.256	0.322

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table VIII: Regressions of the in-area PPP loans on FSS and controls. Columns 1 through 4 use in-county lending. Columns 5 through 8 use in-state lending. Columns 1 and 5 report results from OLS bank-level regression of log in-area PPP loans. Columns 2 through 4 and 6 through 8 report results of bank-geography-level OLS regressions of log in-area PPP loans. Errors are clustered at the bank-level for bank-geography OLS regressions.

	PPP In County				PPP In State			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Ln(Loan)	Ln(Loan)	Ln(Loan<1m)	Ln(Loan≥1m)	Ln(Loan)	Ln(Loan)	Ln(Loan<1m)	Ln(Loan≥1m)
FSS	-0.000961	-0.00841	-0.00668*	0.0103***	-0.00273	-0.00279	-0.00307	0.0131***
	(0.00270)	(0.00513)	(0.00392)	(0.00315)	(0.00415)	(0.00296)	(0.00291)	(0.00353)
$Ln(Emp_{t-2})$	0.218***	-0.161	-0.167	-0.0868	-0.130	-0.00737	0.0107	-0.311***
	(0.0723)	(0.149)	(0.159)	(0.0810)	(0.0796)	(0.106)	(0.110)	(0.0988)
$Ln(CoreDep_{t-2})$	0.735***				0.495***			
	(0.201)				(0.160)			
$Ln(Eq_{t-2})$	-0.326***	-0.232	-0.0275	-0.00523	0.0994	-0.324***	-0.240***	-0.00365
	(0.0910)	(0.204)	(0.130)	(0.101)	(0.107)	(0.0961)	(0.0857)	(0.0800)
$Ln(CI_{t-2})$	0.199***	0.0760	0.123**	0.164***	-0.108***	0.193***	0.196***	0.255***
	(0.0244)	(0.0627)	(0.0539)	(0.0273)	(0.0288)	(0.0302)	(0.0274)	(0.0258)
$Ln(Branch_{t-2})$	0.235***				0.171***			
	(0.0549)				(0.0491)			
$Ln(Commitment_{t-2})$	0.244***	0.254***	0.212***	0.139***	-0.0260	0.301***	0.289***	0.238***
	(0.0342)	(0.0640)	(0.0523)	(0.0528)	(0.0424)	(0.0345)	(0.0344)	(0.0377)
$Ln(Asset_{t-2})$	-0.431*	-0.0679	-0.275	-0.303**	-0.412*	-0.274*	-0.367**	-0.213*
	(0.229)	(0.283)	(0.224)	(0.134)	(0.222)	(0.155)	(0.147)	(0.128)
PPP_Demand	2.855***				1.850***			
	(0.524)				(0.669)			
COVID_Exposure	-2.529***				1.420*			
	(0.771)				(0.843)			
$Ln(CountyDep_{t-2})$		0.478***	0.492***	0.181***				
		(0.0389)	(0.0390)	(0.0190)				
$Ln(CountyBr_{t-2})$		0.481***	0.501***	0.282***				
		(0.0574)	(0.0466)	(0.0282)				
$Ln(StateDep_{t-2})$						0.403***	0.399***	0.299***
						(0.0492)	(0.0504)	(0.0364)
$Ln(StateBr_{t-2})$						0.484***	0.517***	0.267***
						(0.0646)	(0.0646)	(0.0452)
Constant	-1.641***	-0.992	-0.578	-0.627	0.945	1.325	1.734*	-4.131***
	(0.573)	(1.575)	(1.666)	(0.521)	(0.668)	(0.889)	(0.908)	(0.692)
Observations	2,961	19,632	19,632	19,632	2,961	4,394	4,394	4,394
R-squared	0.656	0.667	0.739	0.618	0.019	0.695	0.720	0.693
County FE	NO	YES	YES	YES				
State FE					NO	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table IX: Average Reported Subitems of Other Noninterest Expenses from Schedule RI-E, as a fraction of total other noninterest expenses for year ends 2016-2019. Note that other noninterest expense subitems may be negative. Banks are not required to report subitems of Other Noninterest Expenses if they are either (1) less than $100,000 or (2) less than 7 percent (in absolute terms) of total other noninterest expenses.

	mean	p50	sd	count	nonzero	pctnonzero
Data Processing	0.1905	0.1905	0.7885	22125	17942	0.811
Advertising and Marketing	0.0497	0.0328	0.3544	22125	12643	0.571
Director Fees	0.034	0	0.1915	22125	10150	0.459
Stationary, Printing	0.0177	0	0.0637	22125	8497	0.384
Postage	0.0108	0	0.0363	22125	7537	0.341
Legal	0.0179	0	0.1456	22125	7682	0.347
Telecom	0.0268	0	0.3116	22125	9590	0.433
Acct and Auditing	0.0349	0	0.2565	22125	10534	0.476
Consulting and Advising	0.0247	0	0.0696	22125	7254	0.328
ATM Interchange	0.0376	0	0.0746	22125	9013	0.407
OREO expenses	0.0164	0	1.093	22125	4005	0.181
Other Ins Expenses	0.0076	0	0.1464	22125	3542	0.16

Table X: Regressions of bank-level PPP outcomes on alternative measures of bank technology plus bank controls. Columns 1 through 4 use log other non-interest expense as a proxy for bank technology. Columns 5 through 8 use log data processing expense as a proxy for bank technology. Columns 1 and 5 report results of logistic regressions using a binary variable equal to 1 if a bank made any PPP loans and 0 otherwise as an outcome variable. Columns 2 and 6 report results of OLS regressions using log PPP loans as an outcome variable, using only those banks with nonzero PPP loans. Columns 3 and 7 report results of OLS regressions using bank-level PPP county concentration as an outcome variable. Columns 4 and 8 report results of OLS regressions using bank-level PPP county concentration as an outcome variable, using those banks with branches in a single county.

VARIABLES	(1) Pr(PPP>0)	(2) Ln(Loan)	(3) County HHI	(4) County HHI	(5) Pr(PPP>0)	(6) Ln(Loan)	(7) County HHI	(8) County HHI
Ln(OthNonIntX$_{t-2}$)	-0.859***	0.125**	-0.0599***	-0.0933***				
	(0.164)	(0.0494)	(0.00948)	(0.0197)				
Ln(DataProc$_{t-2}$)					-0.108	0.0831***	-0.0153***	-0.0274**
					(0.117)	(0.0273)	(0.00500)	(0.0112)
Ln(Emp$_{t-2}$)	0.596***	0.304***	-0.00203	0.00553	0.0122	0.403***	-0.0412***	-0.0585**
	(0.215)	(0.0812)	(0.0117)	(0.0220)	(0.224)	(0.0838)	(0.0125)	(0.0248)
Ln(CoreDep$_{t-2}$)	0.864*	-0.0786	0.164***	0.155***	1.506***	-0.0970	0.198***	0.218***
	(0.517)	(0.232)	(0.0217)	(0.0317)	(0.444)	(0.261)	(0.0255)	(0.0442)
Ln(Eq$_{t-2}$)	-0.219	-0.287***	0.00426	-0.0124	-0.139	-0.307***	0.0235	0.0319
	(0.230)	(0.0809)	(0.0142)	(0.0265)	(0.253)	(0.0874)	(0.0159)	(0.0312)
Ln(CI$_{t-2}$)	0.331***	0.245***	-0.0204***	-0.0350***	0.333***	0.253***	-0.0212***	-0.0347***
	(0.0518)	(0.0222)	(0.00413)	(0.00708)	(0.0569)	(0.0240)	(0.00449)	(0.00766)
Ln(Branch$_{t-2}$)	0.446***	0.101**	0.0479***	0.0728***	0.438***	0.0239	0.0477***	0.0829***
	(0.121)	(0.0500)	(0.00798)	(0.0140)	(0.139)	(0.0553)	(0.00943)	(0.0168)
Ln(Commitment$_{t-2}$)	0.387***	0.226***	-0.000789	0.00298	0.460***	0.229***	0.000530	0.00980
	(0.0785)	(0.0355)	(0.00604)	(0.00993)	(0.0832)	(0.0413)	(0.00675)	(0.0117)
Ln(Asset$_{t-2}$)	-0.879	0.164	-0.123***	-0.0696	-1.721***	0.204	-0.182***	-0.187***
	(0.685)	(0.250)	(0.0302)	(0.0520)	(0.592)	(0.270)	(0.0349)	(0.0672)
PPP_Demand	-1.989*	1.771***	0.256***	0.302	-1.961	1.587***	0.287***	0.235
	(1.187)	(0.456)	(0.0964)	(0.187)	(1.302)	(0.502)	(0.104)	(0.198)
CountyHHI_Dep			0.551***				0.537***	
			(0.0134)				(0.0149)	
COVID_Exposure	-0.988	-2.047***	-0.578***	-0.652***	0.745	-1.632***	-0.580***	-0.718***
	(1.753)	(0.523)	(0.102)	(0.212)	(1.848)	(0.559)	(0.115)	(0.238)
Constant	1.480	-0.323	-0.000337	0.466***	-0.689	-0.231	-0.0796	0.317
	(1.480)	(0.541)	(0.0853)	(0.150)	(1.783)	(0.586)	(0.0997)	(0.193)
Observations	3,578	3,093	3,093	1,062	2,939	2,582	2,582	841
R-squared		0.671	0.526	0.160		0.640	0.501	0.126

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table XI: Regressions of bank-level PPP outcomes on FSS plus alternative measures of bank technology plus bank controls. Columns 1 through 3 use log other non-interest expense as an alternative proxy for bank technology. Columns 4 through 6 use log data processing expense as an alternative proxy for bank technology. Columns 1 and 3 report results of logistic regressions using a binary variable equal to 1 if a bank made any PPP loans and 0 otherwise as an outcome variable. Columns 2 and 5 report results of OLS regressions using log PPP loans as an outcome variable, using only those banks with nonzero PPP loans. Columns 3 and 6 report results of OLS regressions using bank-level PPP county concentration as an outcome variable.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Pr(PPP>0)	Ln(Loan)	County HHI	Pr(PPP>0)	Ln(Loan)	County HHI
FSS	-0.00620	0.00920***	-0.00139***	0.00114	0.0123***	-0.00176***
	(0.0104)	(0.00269)	(0.000420)	(0.0118)	(0.00299)	(0.000460)
Ln(OthNonIntX$_{t-2}$)	-0.971***	0.0971*	-0.0524***			
	(0.170)	(0.0568)	(0.0105)			
Ln(DataProc$_{t-2}$)				-0.116	0.0781***	-0.0143***
				(0.124)	(0.0276)	(0.00492)
Ln(Emp$_{t-2}$)	0.931***	0.336***	0.000860	0.287	0.398***	-0.0350***
	(0.239)	(0.0893)	(0.0127)	(0.245)	(0.0889)	(0.0126)
Ln(CoreDep$_{t-2}$)	0.977**	0.126	0.202***	1.191***	-0.110	0.219***
	(0.413)	(0.250)	(0.0217)	(0.422)	(0.268)	(0.0249)
Ln(Eq$_{t-2}$)	-0.102	-0.287***	0.00799	-0.136	-0.327***	0.0213
	(0.235)	(0.0828)	(0.0147)	(0.271)	(0.0908)	(0.0165)
Ln(CI$_{t-2}$)	0.299***	0.240***	-0.0188***	0.308***	0.249***	-0.0195***
	(0.0538)	(0.0232)	(0.00422)	(0.0590)	(0.0248)	(0.00458)
Ln(Branch$_{t-2}$)	0.311**	0.0218	0.0454***	0.343**	-0.0367	0.0483***
	(0.140)	(0.0526)	(0.00868)	(0.157)	(0.0620)	(0.00989)
Ln(Commitment$_{t-2}$)	0.554***	0.243***	-0.00398	0.557***	0.244***	-0.00231
	(0.0764)	(0.0377)	(0.00651)	(0.0870)	(0.0428)	(0.00701)
Ln(Asset$_{t-2}$)	-1.386**	-0.0260	-0.165***	-1.713***	0.233	-0.200***
	(0.571)	(0.257)	(0.0309)	(0.565)	(0.274)	(0.0351)
PPP_Demand	-2.541**	1.740***	0.240**	-2.177	1.798***	0.258**
	(1.253)	(0.462)	(0.0982)	(1.351)	(0.512)	(0.106)
CountyHHI_Dep			0.550***			0.535***
			(0.0135)			(0.0150)
COVID_Exposure	0.00273	-1.711***	-0.572***	1.148	-1.467***	-0.596***
	(1.726)	(0.515)	(0.104)	(1.886)	(0.566)	(0.118)
Constant	3.913**	-0.470	-0.0101	1.467	-0.381	-0.0856
	(1.616)	(0.581)	(0.0909)	(1.884)	(0.621)	(0.103)
Observations	3,382	2,959	2,959	2,798	2,481	2,481
R-squared		0.676	0.536		0.645	0.514

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table XII: County-level regressions of PPP outcomes on county demographic information and bank competitive environment. Columns (1) and (2) report OLS estimates of the proportion of PPP lending made from out of county as the dependent variable, without and with county-level demographics, respectively. Columns (3) and (4) report OLS estimates of the proportion of county PPP lending made by fintechs as the dependent variable, without and with county-level demographics, respectively. Columns (5) and (6) report OLS estimates of the proportion of PPP lending made by out-of-area technologically savvy community bank (less than $10 billion in assets and top 95th percentile FSS) as the dependent variable, without and with county-level demographics, respectively. Columns (7) and (8) report OLS estimates of the proportion of PPP lending made by credit unions as the dependent variable, without and with county-level demographics, respectively. For the purposes of this table, PPP loans made by lenders not designates as banks, credit unions, or fintechs are excluded from the analysis (this excludes less than 1% of all PPP Loans and less than 10% of all nonbank loans). All fintech are assigned to be out of area. Errors clustered are at the state level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	% Out of County	% Out of County	% Fintech	% Fintech	% TechBanks	% TechBanks	% CU	% CU
Cnty Bank Tech	-0.00229***	-0.00223***	-0.000461**	-0.000400**	-0.000338*	-0.000300	0.000321	0.000317
	(0.000829)	(0.000736)	(0.000181)	(0.000163)	(0.000200)	(0.000192)	(0.000266)	(0.000268)
Cnty Bank Size	0.0311***	0.0187***	0.00546***	0.00377***	0.00162**	0.000576	-0.00101	-0.00171
	(0.00450)	(0.00490)	(0.000857)	(0.000618)	(0.000763)	(0.000916)	(0.00137)	(0.00132)
Log(Branches)	-0.0663***	-0.168***	0.00348***	-0.00619**	-0.00462***	-0.0105***	-0.0263***	-0.0325***
	(0.00732)	(0.0124)	(0.00103)	(0.00250)	(0.00115)	(0.00349)	(0.00356)	(0.00471)
Cnty Dep HHI	0.173***	0.140***	0.0108*	0.00904	0.0165*	0.0158*	-0.0337***	-0.0344***
	(0.0403)	(0.0400)	(0.00573)	(0.00589)	(0.00875)	(0.00864)	(0.00563)	(0.00571)
Log(CU Branches)	0.00239	-0.0150**	0.00246*	0.000676	0.000195	-0.000915	0.0453***	0.0439***
	(0.00646)	(0.00610)	(0.00136)	(0.00137)	(0.00121)	(0.00148)	(0.00432)	(0.00421)
Log(Population)		0.125***		0.00985***		0.00593**		0.00772**
		(0.0150)		(0.00243)		(0.00283)		(0.00305)
% Urban		-0.000545*		3.62e-05		4.39e-05		2.39e-05
		(0.000297)		(5.27e-05)		(5.99e-05)		(4.54e-05)
% age65		0.0618		-0.0416**		-0.0101		0.0513
		(0.131)		(0.0179)		(0.0213)		(0.0383)
2020Q2 Emp Gr		-0.00134		-0.000486		-0.000207		0.000569
		(0.000985)		(0.000349)		(0.000183)		(0.000393)
Constant	0.0616	-0.811***	-0.0122	-0.0629***	-0.000556	-0.0338	0.0701***	0.00635
	(0.0573)	(0.132)	(0.0109)	(0.0225)	(0.00865)	(0.0239)	(0.0147)	(0.0316)
Observations	2,765	2,762	2,765	2,762	2,765	2,762	2,765	2,762
R-squared	0.279	0.346	0.473	0.486	0.128	0.133	0.500	0.502
State FE	YES	YES	YES	YES	YES	YES	YES	YES

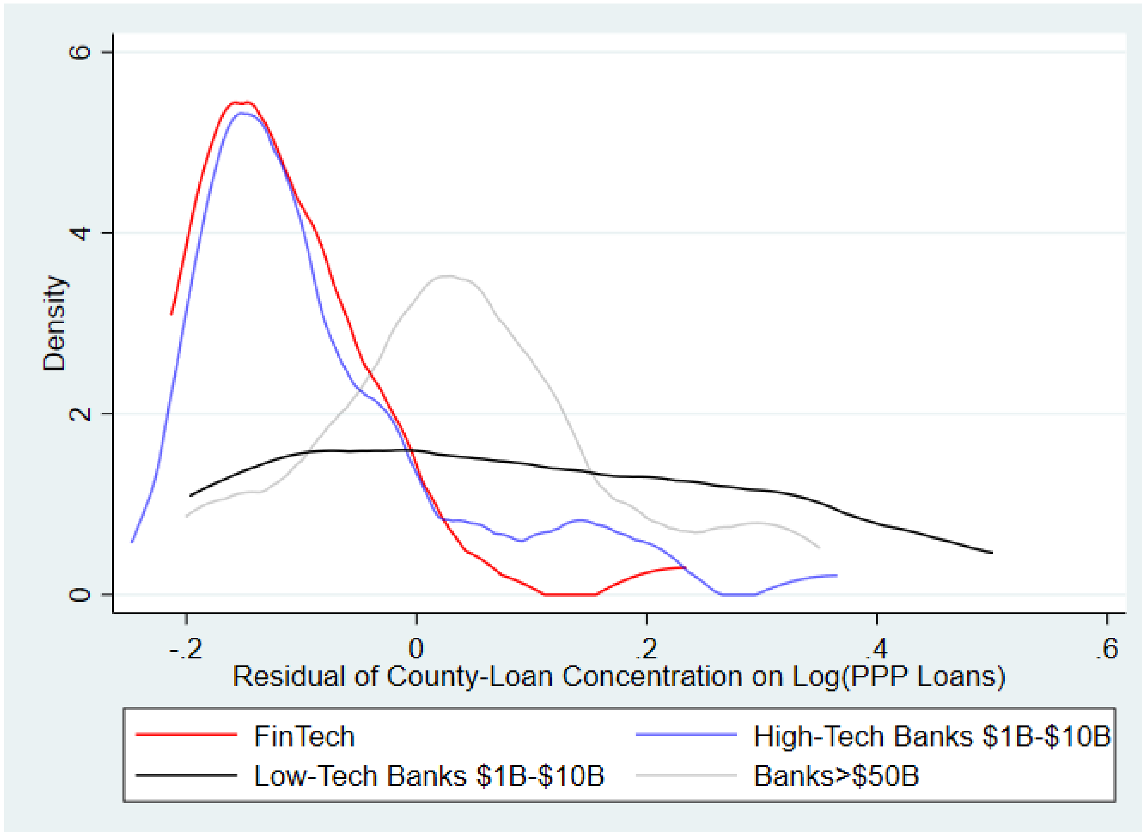


Figure I: Kernel Density of PPP Loan Concentration by Lender Type. The figure plots kernel densities of residuals from a lender-level OLS regression of county-loan HHI on a quadratic expression of log PPP loans for lenders with at least 500 loans. Assets are as of year-end 2019. High-technology banks are those in the top five percentiles of FSS. Low-technology banks are those below the 50th percentile FSS. Negative residual values indicate more geographic dispersion of PPP loans, while positive values indicate more geographic concentration of PPP loans.

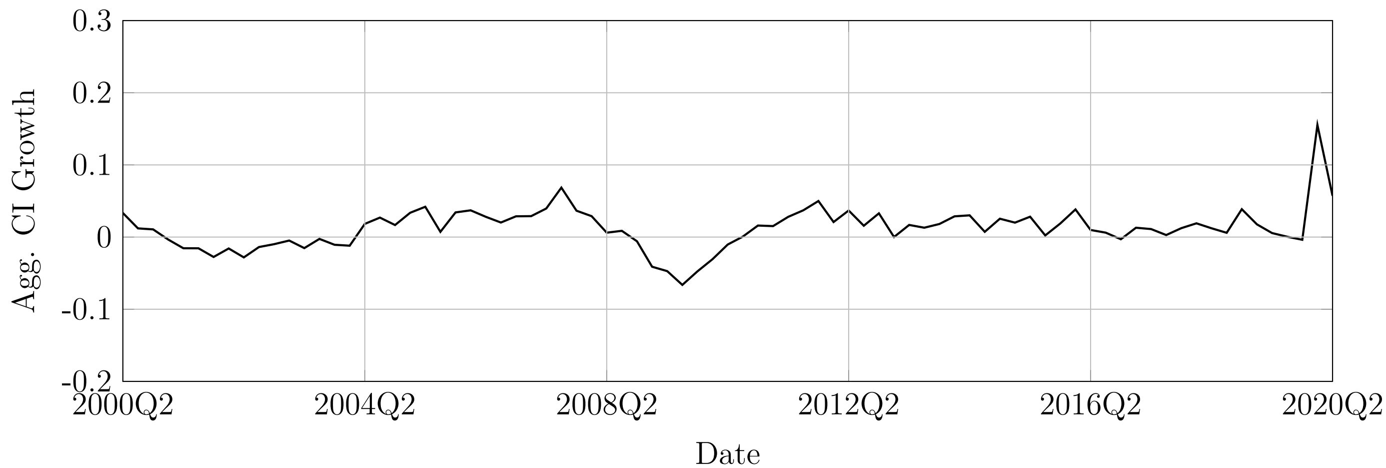


Figure II: Quarterly C&I Loan Growth, 2000Q2-2020Q2. Source: FDIC Quarterly Banking Profile.

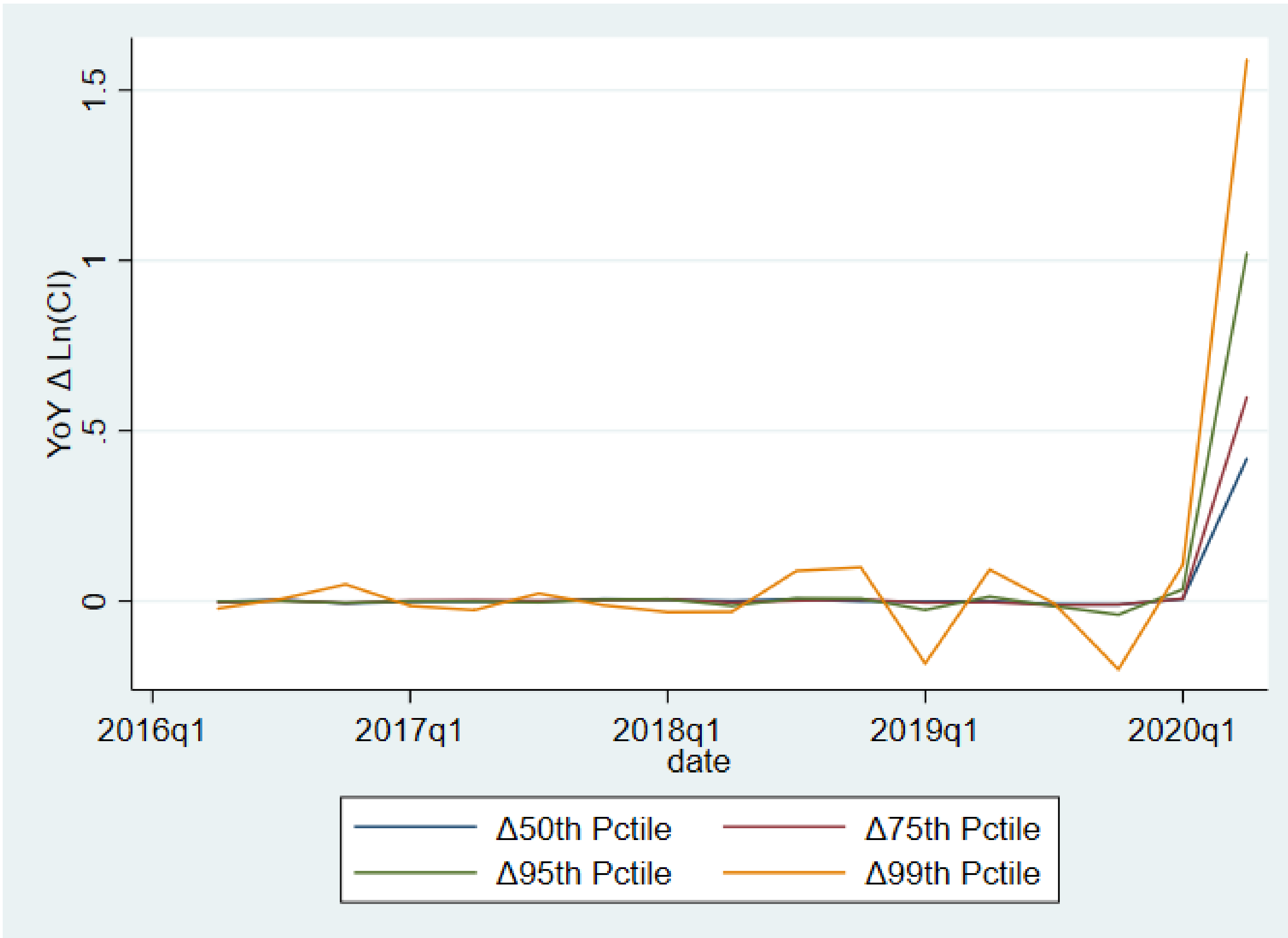


Figure III: C&I lending growth relative to lending growth one year prior, by percentile of growth. Source: Call Reports.

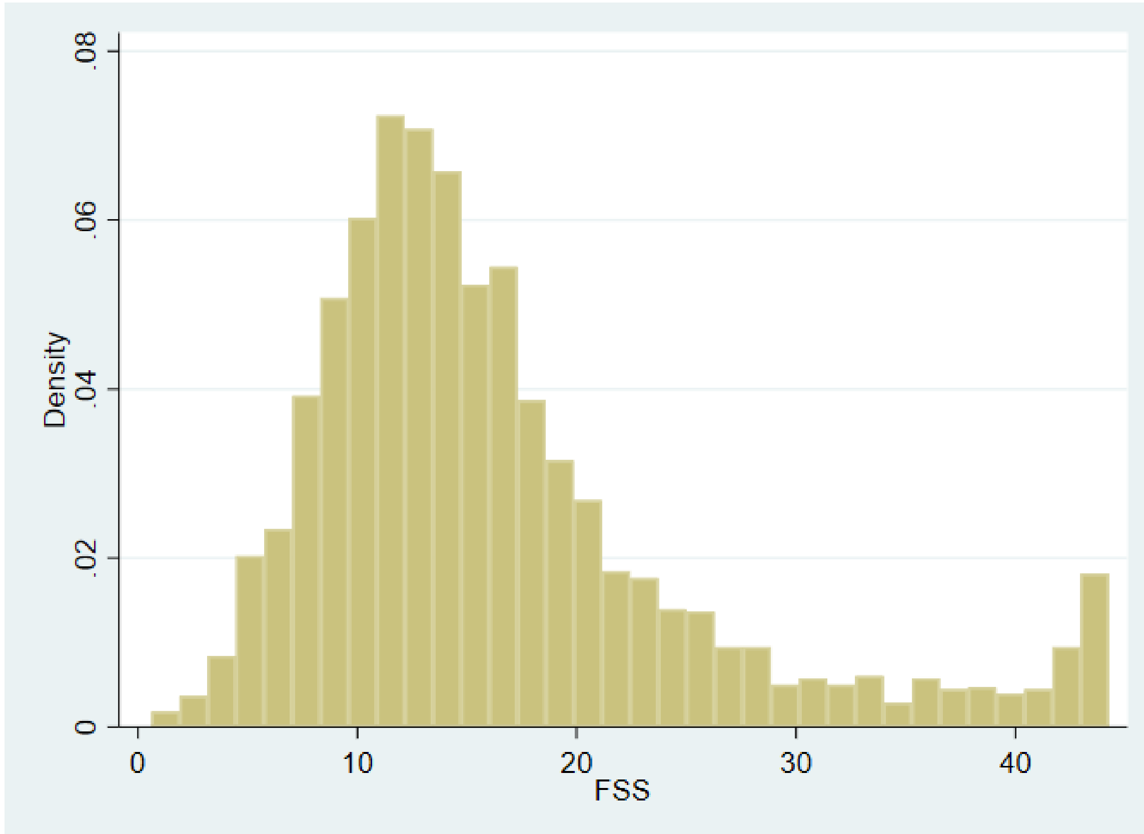
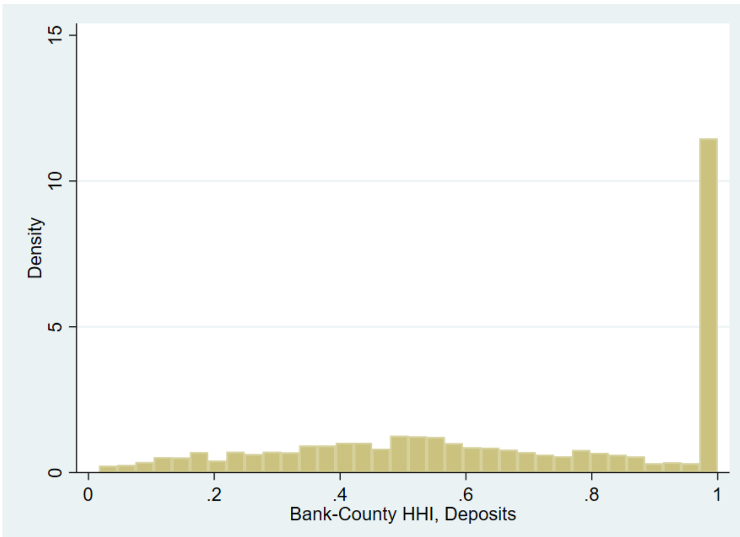
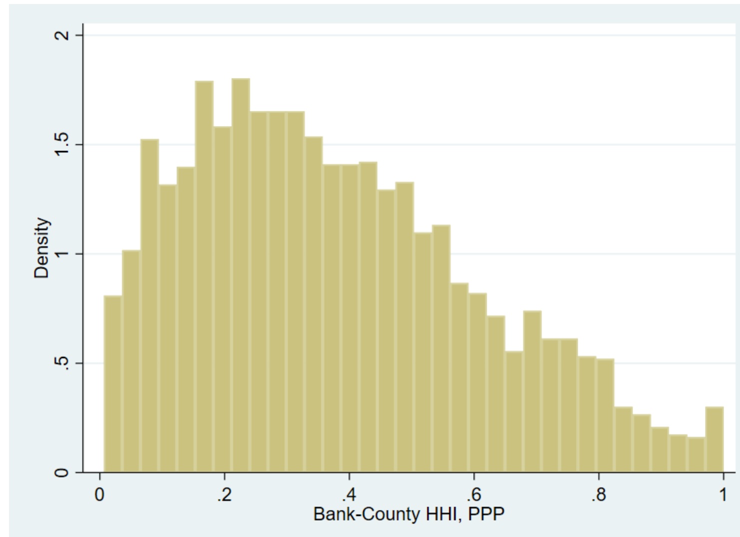


Figure IV: Histogram of Fintech Similarity Score (FSS) for subclass-level product installs for banks with PPP lending in 2020Q2.



(a) Deposits



(b) PPP Loans

Figure V: Geographic Concentrations of Bank 2019 Deposits and 2020 PPP loans, restricted to banks in the regression sample with PPP loans. Panel (a) plots a histogram of banks' geographic (county) concentration of 2019 deposits measured using HHI, constructed using Summary of Deposits. Panel (b) plots a histogram of banks' geographic (county) concentration of PPP loan measured using HHI, constructed using loan-level data.

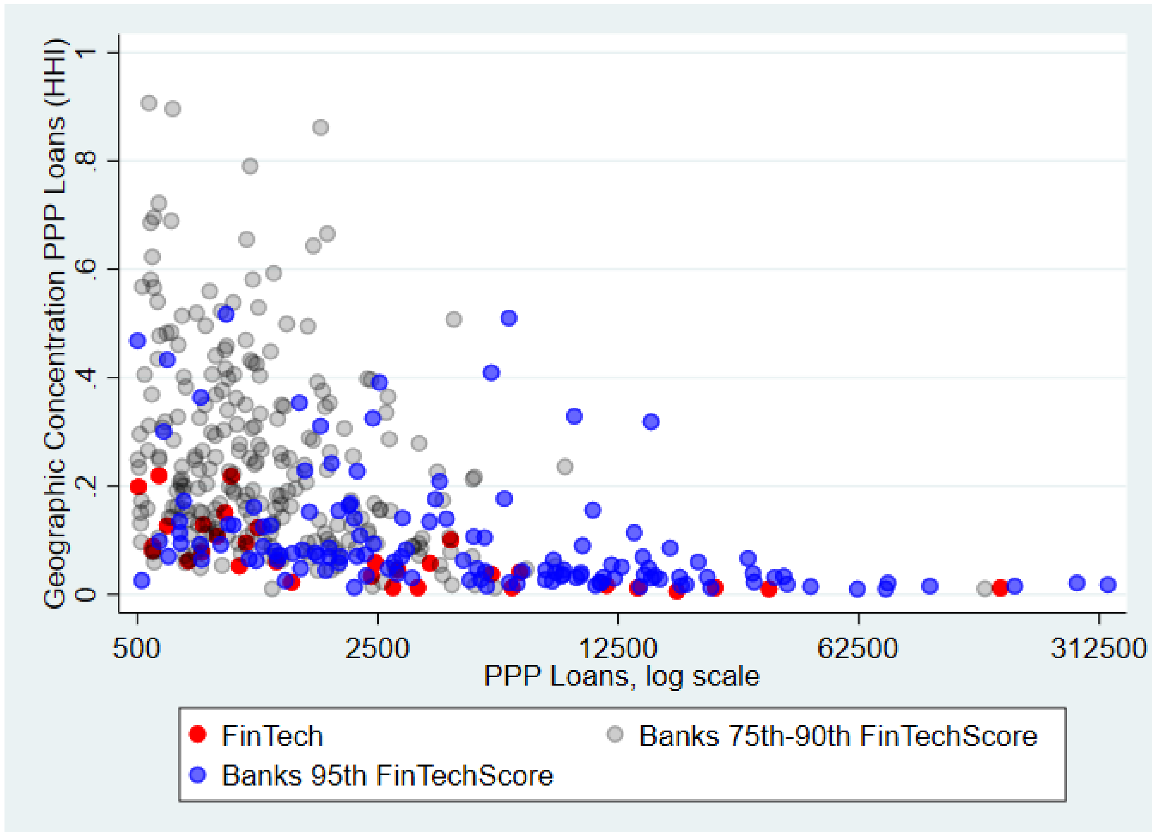


Figure VI: Log PPP Loans (left) and Geographic Concentration of PPP Loans measured by HHI using county shares (right) for nonbank fintech firms and banks according to FSS.

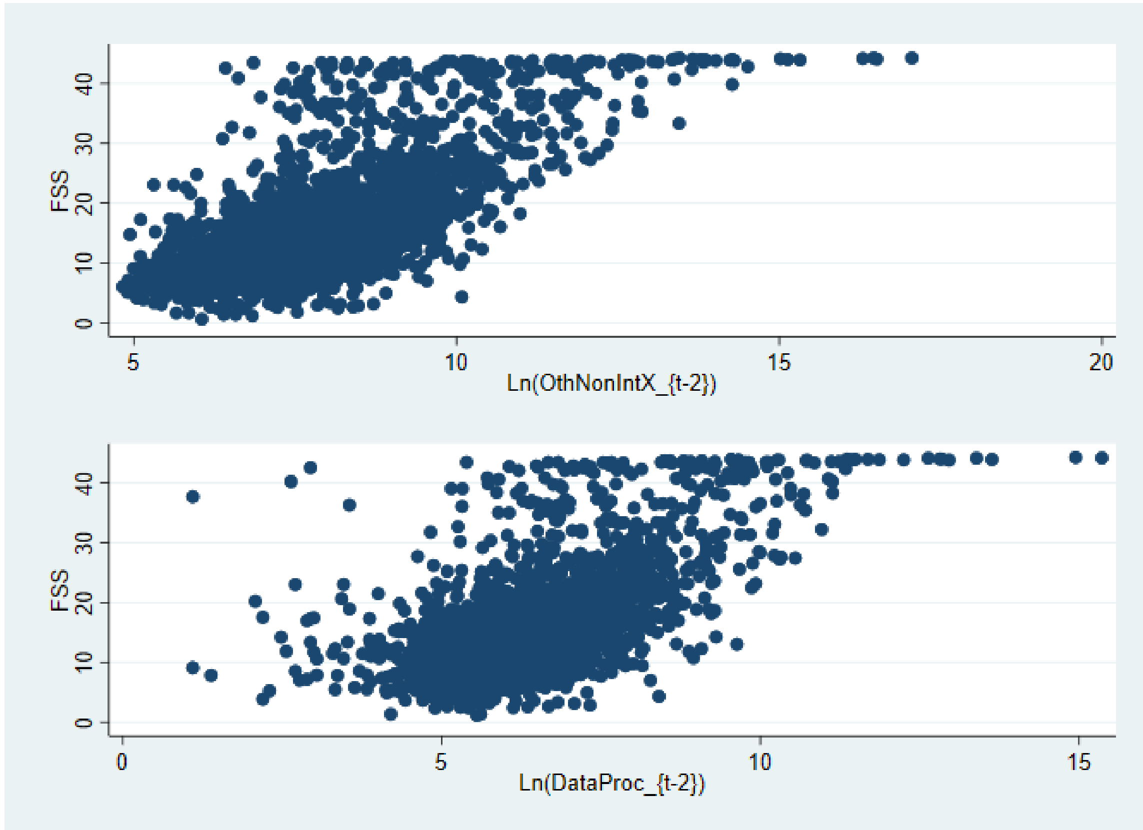


Figure VII: Plot of bank expenses and FSS for banks with PPP lending in 2020Q2. The top panel plots FSS and the log of other noninterest expense. The lower panel plots FSS and the log of data processing expense. Source: Call Reports, Aberdeen data.

Table A.XIII: Regressions of the geographic concentration of bank PPP loans on FSS and bank controls, including PPP loan volume. Table III does not include the control for PPP loan volume. Columns 1 through 3 use a measure of HHI based on bank-level county shares of PPP lending. Columns 4 through 6 use a measure of HHI based on bank-level state shares. The samples in Columns 1 and 4 include all banks with nonzero PPP lending for which other controls are observable. Columns 2 and 5 subset to those banks that with branches in a single geographic area, county and state, respectively. Columns 3 and 6 subset to those banks with county-level Community Reinvestment Act data in 2019.

VARIABLES	(1) County HHI	(2) County HHI	(3) County HHI	(4) State HHI	(5) State HHI	(6) State HHI
FSS	-0.00127***	-0.00337**	-0.00194***	-0.00116**	-0.00124**	-0.00290***
	(0.000395)	(0.00136)	(0.000614)	(0.000501)	(0.000588)	(0.000962)
Ln(PPPLoans)	-0.0585***	-0.0927***	0.0821***	-0.0182**	0.0261**	0.0453**
	(0.00993)	(0.0182)	(0.0258)	(0.00834)	(0.0124)	(0.0226)
$(\text{Ln(PPPLoans)})^2$	0.000676	0.00161	-0.00534***	-0.00451***	-0.00942***	-0.00330**
	(0.000783)	(0.00187)	(0.00158)	(0.000863)	(0.00136)	(0.00160)
$\text{Ln}(\text{Emp}_{t-2})$	-0.0170	-0.00918	-0.0344**	-0.0280**	-0.0177	-0.0259
	(0.0107)	(0.0226)	(0.0151)	(0.0132)	(0.0153)	(0.0206)
$\text{Ln}(\text{CoreDep}_{t-2})$	0.221***	0.251***	0.102***	0.212***	0.187***	0.109
	(0.0231)	(0.0478)	(0.0389)	(0.0312)	(0.0373)	(0.0707)
$\text{Ln}(\text{Eq}_{t-2})$	-0.00122	-0.0191	0.00699	0.0168	0.0126	0.0111
	(0.0144)	(0.0274)	(0.0221)	(0.0151)	(0.0162)	(0.0363)
$\text{Ln}(\text{CI}_{t-2})$	-0.00803*	-0.0144*	-0.0164**	-0.00397	-0.00186	-0.0144
	(0.00427)	(0.00780)	(0.00749)	(0.00451)	(0.00501)	(0.0124)
$\text{Ln}(\text{Branch}_{t-2})$	0.0475***	0.0690***	0.0283**	0.0467***	0.0472***	0.0267*
	(0.00828)	(0.0154)	(0.0123)	(0.00891)	(0.00993)	(0.0154)
$\text{Ln}(\text{Commitment}_{t-2})$	0.00881	0.0216**	0.00608	0.0110	0.0152**	-0.00935
	(0.00622)	(0.0106)	(0.0101)	(0.00688)	(0.00759)	(0.0153)
$\text{Ln}(\text{Asset}_{t-2})$	-0.199***	-0.201***	-0.0735	-0.190***	-0.172***	-0.0647
	(0.0300)	(0.0603)	(0.0453)	(0.0377)	(0.0441)	(0.0737)
PPP_Demand	0.375***	0.324*	0.666***	0.463***	0.362***	0.682**
	(0.0966)	(0.186)	(0.167)	(0.0975)	(0.102)	(0.326)
COVID_Exposure	-0.654***	-0.804***	0.0468	-0.217**	-0.269***	-0.173
	(0.105)	(0.202)	(0.167)	(0.101)	(0.101)	(0.188)
CountyHHI_Dep	0.528***		0.279***			
	(0.0138)		(0.0407)			
CountyCRA_HHI			0.556***			
			(0.0584)			
StateHHI_Dep				0.836***		0.385***
				(0.0244)		(0.0562)
StateCRA_HHI						0.535***
						(0.0513)
Constant	-0.0129	0.424**	-0.541***	-0.212*	0.569***	-0.546**
	(0.0955)	(0.183)	(0.177)	(0.109)	(0.124)	(0.262)
Observations	2,961	966	445	2,961	2,458	445
R-squared	0.569	0.244	0.811	0.492	0.223	0.767

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.XIV: Regressions of financial technology measures on bank and local-area, county-level controls. Columns 1, 2, and 3 explain differences in bank-level FSS, other noninterest expense, and data processing expense, respectively. Sample for each specification is limited to banks with an observed value of the technology measure (and noncensored values for data processing expense) and with PPP lending in 2020Q2.

	(1)	(2)	(3)
VARIABLES	FSS	Ln(OthNonIntX)	Ln(DataProc)
$\text{Ln}(\text{Emp}_{t-2})$	0.822*	0.691***	0.551***
	(0.420)	(0.0461)	(0.0438)
$\text{Ln}(\text{CoreDep}_{t-2})$	-0.902	-0.307***	0.0321
	(1.034)	(0.0549)	(0.108)
$\text{Ln}(\text{Eq}_{t-2})$	0.00669	-0.163***	0.00838
	(0.504)	(0.0329)	(0.0557)
$\text{Ln}(\text{CI}_{t-2})$	0.277**	0.0317***	0.00324
	(0.122)	(0.0107)	(0.0126)
$\text{Ln}(\text{Branch}_{t-2})$	2.597***	-0.127***	-0.0708***
	(0.234)	(0.0191)	(0.0256)
$\text{Ln}(\text{Commitment}_{t-2})$	0.101	-0.0159	-0.000875
	(0.188)	(0.0242)	(0.0232)
$\text{Ln}(\text{Asset}_{t-2})$	2.046	0.875***	0.379***
	(1.355)	(0.0980)	(0.137)
PPP_Demand	0.0598	-1.193***	-1.025***
	(2.800)	(0.160)	(0.315)
COVID_Exposure	2.193	-0.668***	-1.088***
	(4.192)	(0.192)	(0.365)
Constant	-9.832***	-0.490	-1.192***
	(3.367)	(0.433)	(0.349)
Observations	2,961	3,093	2,582
R-squared	0.515	0.949	0.796

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

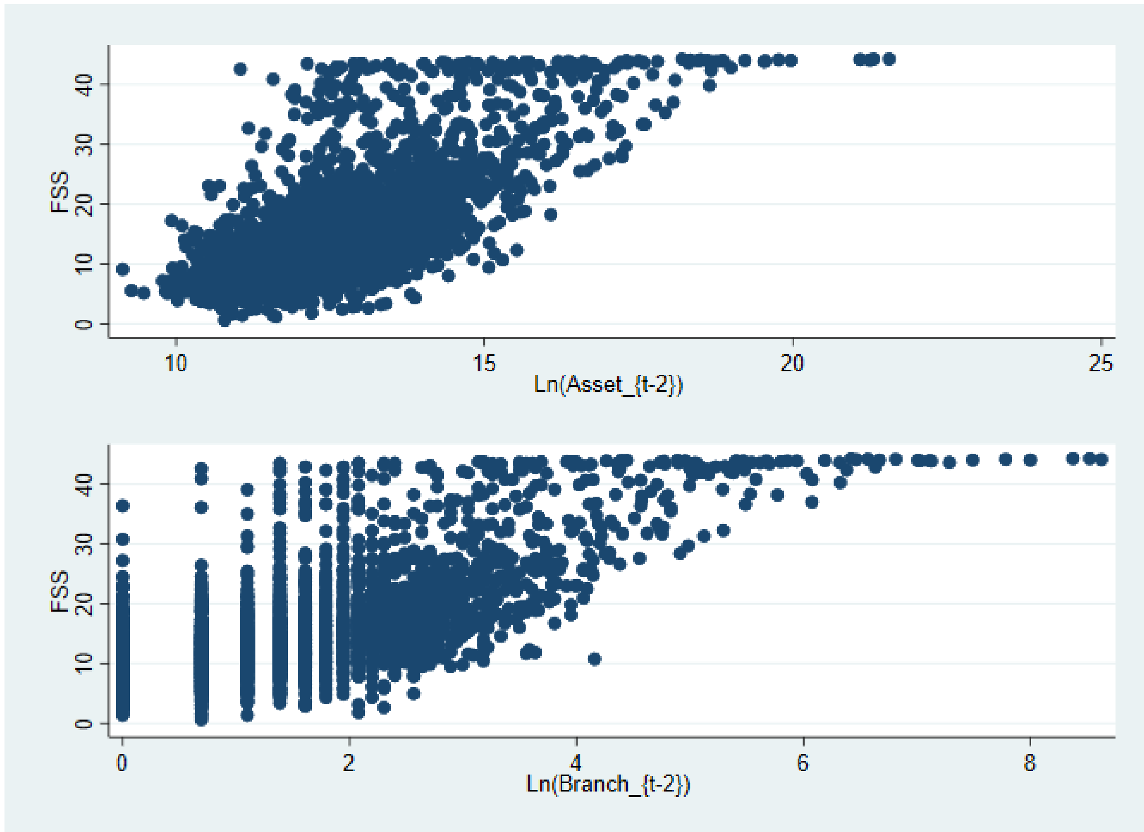


Figure A.VIII: Plot of bank characteristics and FSS for banks with PPP lending in 2020Q2. The top panel plots FSS and the log of total assets. The lower panel plots FSS and the log of number of branches. Source: Call Reports, Aberdeen data.