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Can Banks Lend Like Fintechs? Technology, PPP, and the COVID-19 Pandemic *

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Abstract

Using granular data, we describe the dimensions along which bank technologies differ from fintech competitors and construct a novel measure of a bank's technology based upon its technology overlap with fintech firms. We show that a one standard deviation increase in our financial technology measure is associated with an 8.7 percentage point increase in transaction-based loans associated with the Paycheck Protection Program (PPP) in 2020Q2. Technology enables banks to originate outside of their branch market area and in less concentrated geographies, but does not crowd out in-market lending that is more associated with a physical presence. In a difference-in-differences analysis, we show an outsized increase in small business lending growth in 2020 for mid-sized high tech banks relative to their peers.

Keywords: Banking, Fintech, Technology, Paycheck Protection Program, COVID-19, Commercial & Industrial Lending, Small Business Lending

JEL Codes: G21, G23, O3

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I. Introduction

Financial technology and its role in the financial landscape is prevalent in discussions in the academic literature,[1] popular press,[2], and regulatory communities.[3] Financial technological innovations have factored into consolidation and have given new players a means to enter the lending space.[4] An often-discussed implication of these trends is that small and mid-sized banks, which lack the economies of scale that typically support investments in technology, may face increasing pressure (Berger, Molyneux, and Wilson (2014)).

Amidst the trend of consolidation, smaller banks have maintained market share in small business lending, a market where relationship lending models have so far given them a comparative advantage. Operating in fewer markets, with fewer layers of management makes it easier for loan officers at smaller banks to use local knowledge and personal experience with a borrower to convey soft information for business decisions and underwriting.[5] In contrast, larger banks tend to have a comparative advantage in transactional lending, having developing automated methods to process hard information submitted in loan applications along with credit scores. What are the technological capabilities underlying these differences in lending models? And, if technology leads to more demand for online loan applications and new entrants in small business lending,[6] will smaller banks be ready to compete in terms of

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

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

[3]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.

[4]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)).

[5]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.

[6]E.g., Verhage, Julie and Jennifer Surane. "Technology is allowing both larger banks and fintech players to move into more specialized areas, such as small business lending, that heretofore had been the domain of local banks." *S&P Global* The Future of Banking: The Growth of Technology, 13 Feb. 2019.

transactional lending technology?

Evaluating the ability of smaller banks to compete in the space of transaction-based lending is complicated first by the measurement of technology, second by the challenge of controlling for unobservable differences in credit quality across loans, and third by the endogenous decisions of banks to choose technology given the existing lending opportunities. Our paper uses data previously unexplored in the literature to capture technology and considers an unexpected circumstance where a majority of the small business lending market became transactional. Features of the lending program highlight the role of efficiently processing hard information, rather than differences in monitoring, underwriting, or the interest rates or fees that banks charge. In this way, our analysis focuses on the role of technology in automating the processing of loan applications.

Launched in the early weeks of the onset of the 2020 COVID-19 pandemic in the United States, PPP loans are precisely the information-insensitive, transactional loans that extant theories suggest are the province of larger banks and technology firms (Berger and Udell (1995), Petersen and Rajan (1995)). 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 in terms of underwriting. Furthermore, because funds were potentially limited and due to pressure from borrowers, PPP lending volume depended on rapid processing of application materials.[7] Although larger banks are generally associated with higher levels of transaction based lending, banks with less than $10 billion in assets as of June 2020 made up 40.7 percent share of PPP lending volume and 45.1 percent share of total PPP loans. These market shares were 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

[7] A concern with interpreting PPP lending as a reflection of credit demand is the extent of potentially misreported loans. In one evaluation of misreporting, Griffin, Kruger, and Mahajan (2023) use several metrics to flag loans as suspicious, such as especially high compensation relative to the number of employees. Overall, they identify 12.3 percent of PPP loans as suspicious, with substantially higher rates for loans originated by fintechs as well as for loans originated in the last round of funding. Our analysis focuses on lending differences between banks and does not include the final round of funding. Thus, to the extent that misreported loans do not align with our interpretation, we expect that such loans would make up a relatively small share of the loans that form the basis of our analysis.

portfolio would suggest.[8]

We argue that the 2020 pandemic is a shock that differentially enhanced the value of technology for lending. For example, pandemic-related concerns may have increased the relative value of virtual platforms for borrowers or technology may have been relatively more valuable for lending due to the information insensitivity of PPP loans. 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."[9] Our premise is that prior investments in technology or prior experience with transactional lending would give a lender an edge in the competitive market to originate PPP loans at the start of the pandemic.

Using the product installation data from the Aberdeen Technology Data Cloud (hereafter Aberdeen), we compare and contrast technologies used by banks and fintech firms prior to the pandemic. To our knowledge, we are the first to formally quantify the differences in technologies used by banks and fintech firms.[10] We find that fintech firms are more likely than banks to use business intelligence software, app development, help desk management (such as chatbots), and customer relationship management software than their banking peers. On the other hand, banks are more likely to use local servers, routers, local area networks, and firewalls than their fintech peers.

Taking the proportion of fintechs using a technology as weights, we then construct a novel measure of financial technology, which we call the Fintech Similarity Score (hereafter, FSS). Given that banks have different business models than fintechs, we do not penalize banks for having technologies that are not used by fintechs. Instead, FSS captures the extent to

[8]Source: Call Reports.

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

[10]Also using Aberdeen, 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. He, Jiang, Xu, and Yin (2022) find that demand for mortgage refinancing can drive greater IT spending. In contrast, our analysis focuses on the role of technology in meeting credit demand, particularly when underwriting is a lesser consideration in the context of government guarantees. In addition, we are the first, to our knowledge, to provide evidence of how a bank's use of a wide range of technologies can mimic the capabilities of fintechs.

which banks have the technologies used most commonly by fintech firms. 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).

For our main 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, controlling for an array of 2019 balance sheet variables (for example, bank size). A one standard deviation increase in FSS is associated with a 8.7 percentage point increase in PPP loan volume in 2020Q2. Our finding that technology is associated with reduced loan concentration holds even after controlling for the geographic concentration of a bank's deposits and small business lending in 2019.

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 include alternative measures of bank technology. These alternative measures encompass spending on external services including data processing and are based upon expense information available in quarterly financial statements (Call Reports). FSS and the alternative measures appears to capture distinct aspects of technology, suggesting that there may be multiple technology pathways for achieving similar outcomes.[11]

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 and a set physical presence in terms of branches. While many banks invested in technology and developed partnerships during the pandemic, we expect that those with pre-existing investments would be the most knowledgeable and best positioned for the demands of remote access. Our primary measure of geographic lending concentration is a Herfindahl-Hirschman Index (HHI)

[11] For a more general analysis of how investments in various forms of technology each contributed to greater PPP lending as well as lending at greater distances, in particular for community banks, see Hoople (2021).

of lender-level PPP county-loan concentration.

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 a banks' loan concentrations (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 (defined according to Erel and Liebersohn (2022)), large banks (greater than $50 billion in assets as of year-end 2019), high-technology (top five percent FSS) banks between $1 billion and $10 billion in assets and low-technology (bottom 50 percent 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 (lower HHI) 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 (higher HHI) for a given lender type. Fintech firms, which are thought to operate without a comparable physical presence, 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. Banks between $1 billion and $10 billion in assets and in the bottom 50th percent of FSS are far more geographically concentrated than fintech firms given the number of PPP loans issued. Perhaps more surprising is that technology-heavy banks (in the top five percent of our measure) 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.

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 plays 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 most 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 higher levels of 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).

As technology is an endogenous choice by banks, the estimated relationships from the cross-sectional regressions between PPP lending and bank technology are not necessarily causal. For example, differences in PPP lending during the pandemic may reflect pre-existing differences in lending strategies across banks based on omitted factors correlated with bank technologies. To address this endogenous technology adoption concern, we adopt a difference-in-differences approach, comparing loan growth and loan concentration for banks across technologies, before and after the onset of the pandemic. For the analysis, we rely on publicly available Community Reinvestment Act (CRA) data on small loans to businesses for mid-sized banks ($1.284 billion to $10 billion in assets).[12] The data include both the subset of PPP loans meeting the definition of small business loans for reporting as well as loans made in 2020 outside of the PPP. Our year-by-year estimates (for several years prior to the pandemic) are consistent with the parallel trends assumption that underlies our PPP analysis. Furthermore, we find that in 2020, the number of small business loans made by high-tech midsized banks increased by approximately 45 percent relative to their lower technology peers. In addition, we find that in 2020, the concentration of high-tech banks' small business lending relative to

[12]The CRA data are not available for smaller institutions.

their respective deposit footprints decreased (dispersion increased) relative to their peers.

This research aims to fill a knowledge gap by presenting multiple, quantitative measures of a bank's technical capacity that are not specific to a single technology. Prior innovations studied in the literature include the adoption of Automated Teller Machines (Saloner and Shepard, 1995) and transactional bank websites (DeYoung, Lang, and Nolle, 2007). These innovations and others have become widespread and may have contributed to consolidation and to geographic expansion of banks, through affiliates ((Berger, 2003) (Berger and DeYoung, 2006)). Early adoption varied with the characteristics of a bank (for example, size, extent of branch network, and deposit mix). Other research infers the importance of technology by measuring, for example, the market share of Fintech firms Buchak, Matvos, Piskorski, and Seru (2018). Our research introduces a measure of technology relevant for both non-banks and banks and compares it alongside other measures of technical capacity.

Our paper 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 (2021) and Lopez and Spiegel (2023) find that traditional measures of relationship lending (for example, smaller bank size, prior experience in small business lending, higher loan commitments, and higher core deposits) predict PPP lending. Erel and Liebersohn (2022) 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 technology in meeting bank PPP demand, while also controlling for some of the balance sheet factors included in previous empirical work. Complementing Li and Strahan (2021), 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. We argue that technology can explain up to about one sixth of high-tech banks' PPP loan share.

The rest of the paper is organized as follows. Section II provides some background. 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 discusses the difference-in-differences analysis. Section VII concludes.

II. Background

On January 21, 2020, the Center for Disease Control confirmed the first COVID case in the United States. As awareness of the scale of the pandemic grew, individuals took actions to reduce their individual exposures to the virus and local and state governments took measures to reduce the spread of the virus and the burdens on public health systems. Subsequently, states and territories issued mandatory stay-at-home orders, with the first territory issuing an order on March 15 (Puerto Rico) and the first state order issued on March 19 (California), with other states following suit.[13] By the end of the first quarter in 2020, the federal government of the United States mounted an initial fiscal response.

On March 27, 2020, Congress passed the CARES Act, which included the Paycheck Protection Program (PPP) offering $349 billion in aid to small businesses and administered by the Small Business Administration. The PPP has a number of important institutional details relevant for understanding the factors that drove bank and non-bank participation in the program. Demand for PPP loans at the onset of the program was high and initial funds were dispersed entirely between April 3 and April 16, 2020 (Phase 1). On April 24 the program was extended to $669 billion by the Paycheck Protection Program and Health Care Enhancement Act (Phase 2).[14] Lenders participating in the SBA 7(a) lending program at the time of PPP

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

[14]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.

were automatically approved to make PPP loans on a delegated basis. The CARES Act also enabled the SBA Administrator and Secretary of the Treasury to authorize additional lenders to meet borrower demand. As a result of the institutional features of the program, Phase 1 PPP lenders were predominantly banks (Erel and Liebersohn (2022)) and prior SBA 7(a) participation was a key determinant in PPP lender participation (Lopez and Spiegel (2023), Granja, Makridis, Yannelis, and Zwick (2022)). Given the minimal role of fintechs in Phase 1, we focus on 2020Q2 PPP data overall (including both phases) to facilitate comparisons between banks and fintechs. We end in 2020Q2 to minimize the role of technology adoption decisions made as a result of the pandemic. However, the main results are similar using Phase 1 PPP data. Moreover, we account for prior SBA 7(a) lending. In most cases, the FSS measure appears orthogonal to many other drivers of PPP lending.

Collectively, the pandemic and associated government responses are associated with unprecedented increases to 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).[15] 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. We argue that reduced interest for in-person banking brought about by the pandemic, combined with the PPP, advantaged technology banking solutions relative to physical branches.

[15]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.

III. Data

Our analysis sample of banks derives from quarterly Call Report data, which is also the source for bank full time employment as well as bank balance sheet or financial stock variables including core deposits, equity, C&I lending, loan commitments, and assets for 2019. We consider a set of active banks in 2020Q2. Bank branch locations and the number of branches derive from FDIC Summary of Deposits (SOD) data, reported as of June 30, 2019. We link these data to PPP 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 and to minimize the role of ex-post technology decisions by the bank, we restrict attention to PPP loans made by June 30, 2020.[16] 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.[17] We use the loan-level PPP data, by institution, to construct several measures of lending described in more detail in Section IV.

B. 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. Aberdeen (formerly Harte-Hanks and more recently Spiceworks Ziff Davis) uses web-mining of businesses and employee profiles for data collection

[16]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.

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

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); He, Jiang, Xu, and Yin (2022)), 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.[18] 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 an establishment's business name, address and industry information, to the FDIC SOD data on bank branches.[19] 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). We aggregate establishments with the assumption that a product in use at any establishment is available for that bank as a whole.

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.[20] We restrict attention to 76 fintech firms from the sources, as those relating to consumer finance, business finance, digital banking-related services, or similar lines of businesses based on classification from the source or through a review of the firm's website. 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 link 47 fintech

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

[19] 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.

[20] For example, Kabbage, a business lender based in Atlanta, GA (see CB Insights 2018).

firms to Aberdeen establishment data.

To illustrate differences and similarities in the use of technology between fintechs and banks, we compute the average use rate for each subclass of products by banks and fintechs. From among 183 technology subclasses held by at least one bank, Table I lists the seven technology subclasses used most and least by fintechs, relative to banks, as well as seven intermediate cases (in the middle of the table). The technology with the greatest disparity is "Help Desk Management", a software product used by about three quarters of fintechs and one in twenty banks. Some instances of this technology are for a chatbot to automate customer experience or for an AI-engine that personalizes web content. Other top subclasses for fintechs include business intelligence (e.g. search, analysis, and machine learning), collaboration/integration software (e.g. virtual conferencing, and monitoring web traffic), App development, customer relationship management software, and other business intelligence software for big data and cloud computing.

At the other end of the spectrum are technologies used at least as much, and sometimes more, at banks as at fintechs. These seven include: local area network (LAN), firewall, router, server, and accounting software technologies. Lastly, the seven intermediate technologies include network management and data center software as well as other widely-used business applications. See Appendix Table A.XVI for manufacturer and product examples of each of these cases.

The seven technologies disproportionately used by fintechs reflect web-based marketing, remote capture of borrower information, automated decision making and cloud computing capabilities, all of which are central to the transactional and scalable business model of those nonbank lenders. The seven bank-centric technologies are perhaps indicative of an emphasis on a fixed physical office space and an emphasis on data security. The seven intermediate technologies are typical of office environments (though they are still more often used at fintechs than at banks).

The fintech use rates enter the into our univariate measure of bank technology as weights for those technology subclasses so that banks receive a higher score when they operate technologies used by a larger proportion of fintechs. For each bank, we construct the Fintech Similarity Score, or FSS, as:

$$FSS = \sum_s^S w_s \max_{p \in P_s} I_p \tag{1}$$

$$w_s = \frac{1}{F} \sum_f^F \max_{p \in P_s} I_p. \tag{2}$$

Aberdeen has P products (e.g. Concur Travel - an online booking tool), indexed p, with each product belonging to one of S technology 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 gauge of the importance of those products for financial technology (see Table I). High scores correspond to a bank being more aligned with the technologies that are more prevalent among fintech firms (there is no penalty for having other technologies not present in fintech firms).

C. Local economic factors

In addition to bank employment, the bank balance sheet variables, and number of branches, we include as control variables 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 its branches. 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 growth from 2019Q2 to 2020Q2.[21] That is,

$$Exposure_{c,2020Q2} = \sum_i z_{i,c,2019Q2} \cdot g_{i,2019Q2-2020Q2} \tag{3}$$

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. Employment growth is sourced from the Bureau of Labor Statistics, Quarterly Census of Employment and Wages. 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. Ex-ante exposure to industries that were hard hit by the pandemic strongly predicts subsequent employment outcomes.[22] For each bank, we construct the bank-specific labor demand shocks by taking a deposit-weighted average of the county level exposure variable.

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 match to at least one Aberdeen site and also have data in the Product Install Table for computing FSS. Our analysis mostly focuses on the intensive margin of PPP use. In Table II we present summary statistics for the 87.5 percent of these banks (2,961 in total) that had at least one PPP loan in 2020Q2. Financial stock variables are measured as the average quarterly balance over 2019, branches are measures as of the June 2019 SOD, financial flow variables are measured as the

[21]This is effectively a Bartik instrument. Due to seasonality, especially for harder hit retail and travel industries, this measure is preferred to quarterly employment growth.

[22]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 employment growth measure is approximately 0.5 and the F-statistic is about 40 both with and without state fixed effects and demographic controls - indicating that our exposure measure is associated with changes in local economic outcomes, as expected.

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. 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 the 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.

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, cloud computing), communications (e.g. Virtual Private Networks, phones), services (e.g. personnel management systems, web hosting, accounting), and software (e.g. process automation, digital advertising software, database management software). These components are calculated as Equation 1 except that S is limited to the subclasses comprising a component.

We show how the technology measures relate to one another as well as to total assets and number of branches. Figure A.IX 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 variation 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.[23]

[23]In Appendix Table A.XVIII Column 1, we regress FSS on the bank characteristics used in regression models. Given the known relationship between PPP lending and measures of relationship lending and SBA 7(a) loans, it is important to control for these variables.

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

$$Pr(PPP > 0) = logit(\beta Tech_b + \Gamma Controls_b) \tag{4}$$

$$Ln(PPPLoans) = \beta Tech_b + \Gamma Controls_b + \epsilon_b \tag{5}$$

We include bank balance sheet variables as controls for traditional factors in bank relationship lending (e.g., size, branches, employees, commercial and industrial lending volumes, SBA 7(a) participation) and also include the two location-based controls for local PPP demand and local economic disruption from the pandemic.

In Table III 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 II) is associated with a 8.7 p.p. increase in PPP loan volume in 2020Q2 (that is, $8.64 \times 0.00975 = 0.087$). Thus, it appears that technology may be related to 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 in 2020Q2.

To quantify the magnitude of the effect of technology, we consider the set of high-tech midsize banks used in Figure I with between $1 billion to $10 billion in assets and in the top five percent FSS among all banks. Among those banks for which FSS can be measured, the high-tech midsize banks' assets comprise 1.5 percent of industry assets and 2.7 percent of PPP loans. Given the estimated coefficient on FSS from Column 4 of Table III, we estimate that the collective loan growth for high-tech midsize banks is associated with 16.7 percent more loans relative to the case where the high-tech banks had the average FSS score for banks in the $1 billion to $10 billion range. The difference accounts for 45 bps of PPP loan share, about one sixth, of the total PPP market share for high tech banks.

In Columns 7 through 10, we report results from regressions of the extensive and intensive margins for Phase 1 and Phase 2 of PPP within the second quarter of 2020. Given the rapid onset of the pandemic and the PPP program, it may be the case that technology provided banks a greater advantage in the early weeks of the program. On the other hand, prior relationships and experience with SBA lending may have disadvantaged technology in the provision of Phase 1 PPP loans. We find in Columns 7 and 9 that, consistent with prior literature, SBA 7(a) lending and measures of relationship lending are more strongly associated with participation in PPP in Phase 1 than they are in Phase 2. Columns 8 and 10 similarly show a stronger association with PPP loans and SBA 7(a) participation and existing small-business lending in Phase 1 than in Phase 2. In contrast, similarly to the entire 2020 second quarter sample, FSS is not associated with extensive margin participation in either Phase 1 or Phase 2. Moreover, FSS is strongly associated with PPP lending at a similar magnitude on the intensive margin in both Phase 1 and Phase 2. Given these results, our analysis does not generally subdivide PPP lending across Phases elsewhere in the paper, unless noted otherwise.[24]

[24]There is anecdotal discussion of small banks being more nimble and capable of "punching in" loan applications while larger banks developed systematic solutions. For example, see Henderson, Tim "Small Banks Helped Businesses Win More PPP Loans." *Stateline, an initiative of The Pew Charitable Trusts.* 15 Dec. 2020. We find some evidence of larger banks, in terms of assets, being less likely to participate and originate fewer loans during Phase 1, but we find no effect of assets on loan volume in Phase 2 alone or overall. Banks with more employees (all else equal) also produced larger loan volumes.

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 particularly 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 bank branch deposits and bank PPP loans. In particular, for each bank b we construct:

$$HHI_b = \sum_g \left(\frac{y_{bg}}{\sum_g y_{bg}} \right)^2 \tag{6}$$

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

In Figure V we plot the distribution of banks' county concentrations of deposit-weighted branches (left) and PPP loans (right) for those banks in our regression sample with nonzero PPP lending. Banks with branches or lending in only one county have an HHI of exactly one. While bank branches are heavily concentrated in a small number of counties (the median deposit HHI is 0.668), bank PPP loans are geographically far more diffuse (the median PPP lending HHI is 0.345).[25] The disparity in the diffusion of banks' PPP loan concentrations relative to their physical branch presence suggests that factors beyond physical presence must play a role in bank PPP lending.

We estimate a regression similar to Equation 5, 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 IV, with Columns 1 through 3 measuring concentration by county and Columns 4 through 6 measuring concentration by state.[26] We include a control of banks'

[25] Whereas the average banks' deposit-weighted branch base is spread over 1.5 counties, the average banks' PPP loan portfolio is spread across 3 counties. Among 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 substantially larger, consistent with reporting requirements.

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

pre-existing geographic deposit concentration. 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 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 of that variable) and a decrease in state concentration (from Column 4) of 0.0177 (or 0.0804 standard deviations of that variable). 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 effect 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 from CRA reporting in 2019.[27] CRA data include loans of less than \$1 million to businesses 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 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

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

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. As discussed in the introduction, Figure I demonstrates that conditional on the amount of PPP loans, high FSS banks originated PPP loans diffusely, similar to nonbank fintech lenders, using the classifications of Erel and Liebersohn (2022). In this section, we expand upon the discussion in Figure I to examine the extent to which banks with more technology according to our financial technology measure look like 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 (2022), we also restrict attention to those lenders that issued at least 500 PPP 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 technologies most similar to fintech have PPP loans geographically diffuse similarly to fintechs' PPP loans. Consistent with theories of banks and fintechs, banks with technology less similar to fintechs issue loans in more concentrated geographies.

In Table V 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. Similarly, we include an indicator for banks above the 95th percentile of the FSS distribution, and we exclude from the regression banks with more than $10 billion in assets.[28] 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 term 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 above 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 more than half) when a bank is above 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 (2021) 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:

$$\frac{PPP(OutofArea)_b}{PPP(Total)_b} = \beta Tech_b + \Gamma Controls_b + \epsilon_b. \tag{7}$$

We report results from the OLS regression of Equation 7 in Table VI. In Columns 1

[28]This maintains a consistent measure of banks above the 95th percentile used elsewhere in the paper. Including larger banks, either as part of those banks above the 95th percentile or with a separate dummy variable does not materially affect the results statistically or economically.

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 (2022)) 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 VII. 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. Accounting for the differences in the standard deviation in each component, the effects of the hardware and the software components are comparable. Thus, it appears that hardware (and its associated technologies, such as server operating systems and cloud computing) plays the most important role in the ability of banks to engage in out-of-area lending, with software also playing a significant role.

F. *PPP lending: Out-of-area and in-Area loan quantities*

To unpack the findings of Table VI, 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:

$$Ln(PPP + 1)_b = \beta Tech_b + \Gamma Controls_b + \epsilon_b. \tag{8}$$

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 VIII, 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 level similarly to the specifications used for out-of-area lending. In addition, we exploit the pre-pandemic, in-area bank presence across geographies and estimate a similar specification at the bank-geography level including bank-geography controls for branches and deposits. As above, geographies are defined at the county and state levels. We report the results from the in-area regressions of lending in Table IX.

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 (2021), 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 the proportion of PPP loan out-of-area is primarily driven by increases in out-of-area loans and not through the substitution of in-area loans for out-of-area loans.

In Table X we estimate the relationships between in-area PPP lending and FSS under an alternative definition of in-area. We combine the Summary of Deposits data with SBA

7(a) data to define a bank's in-area PPP lending as the union of counties for which the bank has either a branch or at least one SBA 7(a) loan in 2019. Although the SBA 7(a) data does not capture a bank's entire loan portfolio, the data are systematically available across participating banks and provide a broader perspective of a bank's geographic footprint than relying on just bank branches. We also add controls for SBA 7(a) volumes by county. Consistent with Table IX, Columns 1 and 2 show no relationship between in-county PPP lending and FSS for total number of loans and small loans and Column 3 shows a positive relationship between in-area loans above $1 million and FSS. Columns 4 through 6 find similar results between out-of-state PPP loans and FSS, though the relationship between large loans and FSS is statistically significant at the 10 percent level. Collectively, the results are not consistent with technology leading banks to substitute in-area lending to out-of-area lending.[29]

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 the measures capture different aspects of technology than the product-based measure, FSS, though they may also affect lending outcomes. Whereas we expect that FSS most directly reflects the types of in-house technological capabilities of a bank, the expense measures may reflect both the scale of technology investment and use of external, contracted capabilities (and potentially partnerships).

The 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 sub-items that may relate to technology include advertising and marketing expenses and telecom expenses. Other noninterest

[29]The conclusions are similar when restricting only to banks with SBA loans and when defining in-area lending similarly for banks based on CRA data.

expense also includes research and development costs incurred in the internal development of computer software. The second alternative measure, data processing expenses (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 sub-items, including data processing, may be censored. As of 2018, sub-items 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 non-censored values of data processing expense. From 2016 to 2019, there is a non-censored observation for bank data processing expenses for 81 percent of banks' December Call Report data.[30]

Other noninterest expense is best understood by examining its components. Table XI reports statistics on the breakdown of sub-items in Schedule RI-E relative to other noninterest expense. We also report the count of nonzero observations, and note the exact shares of each sub-item are not certain (and could be higher or lower) due to censoring across each of the sub-items. 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 missing values 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

[30]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.

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.[31]

Table XII reports results equivalent to Table III (for PPP lending and volume) and IV (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 XIII 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 effects that facilitate processing of PPP loans, especially for out-of-area borrowers.

V. County PPP Lending

Our bank-level results suggest that technology heavy banks operate more similarly to fintechs than other banks. Existing literature (Li and Strahan (2021)) shows that local bank presence plays an important role in meeting local PPP demand, suggesting that PPP lending is influenced by prior lending relationships. At the same time, the magnitude of nonbank lenders

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

and out-of-area lending suggests that for some PPP borrowers, local relationships may have played a less important role than technology in selecting a PPP lender.

How does local bank technology affect the composition of PPP lenders in an area? If all borrowers have lexicographic preferences over relationships and technology, then the local presence of a technologically heavy bank has few implications for local PPP lending: Borrowers who prefer local banks do not see technological local banks as providing additional benefit, while borrowers who prefer technology-based lenders do not have a reason to favor a local lender against national technology-based competitors. If instead, some borrowers have smooth preferences over technology and relationships then a local bank that is technologically heavy is consequential to the distribution of PPP lenders in an area. For example, borrowers might substitute out-of-area or fintech lenders to comparable technologically heavy banks that also have a local presence. Meanwhile, PPP borrowers who might otherwise choose a traditional relationship lender might opt instead for a local lender with greater technological capabilities. It is an empirical question to understand whether borrower preferences are such that local technology-heavy lenders substitute for borrowers who would otherwise choose a technology-heavy lender, a relationship lender, or both.

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 include county aggregates of bank branches, credit union branches, and the county-level bank-deposit HHI (where county-shares are calculated at the bank level). We also incorporate demographic data such as the county population, percent population in urban areas, percent 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), 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. For the purpose of calculating shares, we exclude non-fintech nonbanks, as well as banks that we are unable to match to Aberdeen Product Install tables.

In Table XIV we report the results of county-level OLS regressions of the relative proportion of county lending met by different lenders. 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. Together, Columns (1) through (4) suggest that local bank technology complements local branch presence for a subset of borrowers who might otherwise prefer an out-of-area PPP or fintech lender. In contrast, in Columns (5) and (6) we find that local bank technology does not relate to the proportion of PPP loans made by credit unions, consistent with the view that for PPP borrowers who consider credit unions, bank technology does not have strong complementarities with local presence.

VI. Difference in Differences

Identifying the effect of technology in the distribution of PPP loans is challenging given the endogeneity of technology choices by banks prior to the onset of the COVID-19 pandemic. In this section, we use a difference-in-differences framework to assess the role of technology in supporting banks' distribution of loans during the first calendar year of the pandemic and administration of the PPP.

We use CRA data of small commercial loans at the bank-county level to examine whether changes in trends in bank lending during the pandemic differ for banks with more technology relative to those with less technology. We rely on the public-use CRA data of small loans (less than $1 million) to businesses originated during the calendar year. For 2020, the data include both the subset of PPP loans meeting the reporting criteria, as well as traditional (not PPP) commercial loans that meet the definition. Although the CRA data include loans outside of PPP, we expect that the pandemic increased the relative value of technology in general (for example, due to borrowers increasing their preference for remote interaction during the pandemic), in addition to the specific role that technology may have played in PPP lending.

Because the CRA data are measured at the bank-county level, we merge the data with Summary of Deposits to assess whether bank lending is made in or out of area (based on branch presence in a county). Furthermore, we examine the geographical concentration of a banks' business loans (by number of loans in a county) relative to the concentration to its deposit footprint (by value of deposits in a county), measuring both with HHI.

A limitation of the CRA data is that they are not generally available for small banks (less than $1.284 billion for 2019). Consequently, we are not able to examine whether small banks' technology profiles are associated with differences in lending subsequent to the onset of the pandemic. Because the largest banks are generally all associated with high FSS, we restrict attention to banks with available CRA data with less than $10 billion in assets as of the end of 2019. To sharpen the difference between banks' technologies, we segment the population of the banks similarly to Figure I and compare the set of banks in that asset range among the top five percent FSS to those in the asset range among the bottom half FSS. Finally, we restrict attention to only those banks that have non-zero in- and out-of-area loan each period in the sample.

We estimate a difference-in-differences regression of the following form:

$$Outcome_{it} = \beta bank95_i * post_t + \lambda_i + \delta_t + \epsilon_{it} \tag{9}$$

where $Outcome_{it}$ represents total small loan growth, out-of-area small loan growth, in-area small loan growth, and the ratio of loan HHI to deposit HHI. The binary variable $bank95$ is equal to one if the bank is in the top five percent of all banks' 2019 FSS and zero otherwise. The binary variable $post_t$ is equal to one for the year 2020 and zero otherwise, with the sample period of 2017 to 2020. We use both a pooled-sample specification (four years of growth) and a collapsed-sample specification, taking the average values in the pre-period for each bank (resulting in two time periods: pre vs. post, see Bertrand, Duflo, and Mullainathan (2004)).

In Figure VIII, we examine the validity of the parallel trends assumption by plotting the coefficients of a pooled-sample version of Equation 9 interacting $bank95$ with each year in the sample (confidence intervals are shown at the 90 percent level). For the case of total loan growth, out-of-area loan growth, and in-area loan growth, there is little evidence of a pre-2020 difference in trend. For the ratio of loan HHI to deposit HHI, there is a slight visual trend prior to 2019, though it is not statistically significant. We conclude based on the graphical and statistical evidence that parallel trends is not an unreasonable assumption: that in the absence of the pandemic with its associated demands on technology and the guaranteed loan program, trends in loan provision for high technology and other banks would have continued in parallel.

In Table XV, we present results of difference-in-difference regressions. Columns 1 through 4 present results from estimation of the pooled sample, while Columns 5 through 8 present results from estimation of the collapsed sample. Estimates from Columns 1 and 5 suggest that high-tech banks increased total loan origination by 45 percentage points relative to low technology banks. Columns 2 and 6 show that the effect is comparable for out-of-area loan origination relative to in-area loan original (Columns 3 and 7). Columns 4 and 8 show that the concentration of high technology banks' lending relative to their deposit footprints fell by 6.8 and 7.6 percent, respectively, relative to lower technology banks. In fact, loan concentration relative to deposit concentration for high technology banks fell by 2.9 percentage points from 2019 to 2020, while increasing by 3.7 percentage points at lower technology banks over the same period (not shown). Finally, in Columns 9 and 10, we include a separate interaction term between a bank's prior SBA 7(a) data and 2020. The SBA 7(a) term interacted with the post indicator accounts for the possibility that high-tech banks changed their lending patterns as a result of prior SBA 7(a) lending rather than the proposed technology mechanism. Column 9 shows that prior technology, but not prior SBA 7(a) lending accounts for changes in bank loan growth in 2020. Meanwhile, Column 10 shows that prior technology, but not prior SBA 7(a) lending also accounts for changes in bank loan dispersion in 2020 relative to prior years.

Notwithstanding our analysis, it is possible that the unobserved heterogeneity driving bank technology decisions also drive differential responses to the unique events surrounding the pandemic and the associated government response. However, the difference-in-differences results suggest that technology or the organizational structures that support technology had a meaningful role in the differential responses of banks to the 2020 pandemic.

VII. Conclusion

What role might technology play in the ability of relationship lenders to succeed in transactional lending amid the rise of fintech firms? To answer this question, we focus on a transactional lending program during the pandemic and advance the discussion of bank technology on a number of dimensions.

First, we use a granular data set to quantify the technologies that differentiate fintech lenders from banks. We find, for instance, that fintechs are more likely to use or develop automation tools such as business analytics software, chatbots, customer relationship management software, and to make use of cloud computing systems. Second, we then construct a novel measure of bank technology, the Fintech Similarity Score, that captures whether banks have adopted technologies most commonly found in their fintech competitors. We find considerable variation in the measure for small and midsized banks and show that it is related, but distinct, from balance sheet measures that capture third-party outsourcing of technology. Third, we show that higher technology banks, as measured with FSS, provided more PPP loans at the onset of the pandemic relative to lower technology peers, with the increase in loans driven through higher out-of-area lending and not at the expense of in-area lending. We find that technology is positively associated with more diffuse geographic lending and that greater technology for in-area banks in a county is associated with lesser reliance for out-of-area PPP lenders or fintech lenders. Last, we show using a difference-in-differences approach that higher technology mid-sized banks' loan growth increased by 45 percentage points in 2020 relative to their mid-sized peers and pre-pandemic trends.

Our quantification of the scope of bank technology is novel in the literature and our analysis shows that the fintechs' technologies are also featured at the banks most successful in transactional lending. By demonstrating that both large and smaller banks can employ a wide range of technologies and use them to make loans, we show that size is not a prerequisite for technology-based lending. We also show that technologically advanced banks may maintain an emphasis on lending in their local area. Lastly, we show multiple channels by which banks may succeed at transactional lending, with spending on external data processing as well qualitative advantages in technology both having independent and additive effects on lending outcomes at the beginning of the PPP program. Together, our analysis suggests that, while technical advances may lead to a greater role for transactional lending, banks of all sizes may deploy the latest technologies alongside other lending models.

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Table I: Bank and fintech usage rates of technology subclasses, as well as the difference in usage of fintechs relative to banks. Use constitutes any establishment of a bank or fintech using any product in a subclass in 2019 as documented by Aberdeen. Rates report average usage across all banks and across all fintechs. Table rows are drawn from the set of product subclasses that are used by at least 5 percent of banks and 5 percent of fintechs and that are also used by at least 20 percent of either banks or fintechs. From those subclasses with substantive usage (67 out of 183 subclasses), the table presents the seven subclasses with the greatest use by fintechs relative to banks (top seven rows), the seven subclasses with the least use by fintechs relative to banks (bottom seven rows), and for seven intermediate subclasses. Product class and subclass definitions are from Aberdeen. Notes are further explanation by the authors based on review of product-level data (otherwise NA, if Aberdeen description is sufficient).

Class	Subclass	Bank	Fintech	Diff.	Notes
Software	Help Desk Management	0.058	0.745	0.686	Automated support including chatbots
Analytics	Business Intelligence (BI)	0.150	0.745	0.595	Search, big data analytics, machine learning, visualization
Software	Collaborative/Integration Soft.	0.154	0.745	0.591	Online transaction processing, conferencing, version control
Software Development	App Development	0.166	0.745	0.579	Development tools (e.g. JavaScript debugging)
Software	CRM/SFA Software	0.116	0.681	0.565	Automate and record all the stages of a sales process
Software	BI Soft.	0.143	0.681	0.538	Big data, cloud computing, web traffic, behavior analysis
Desktop or Portable PC	Supply Chain Management Soft.	0.182	0.702	0.520	Data warehouse software for querying and analysis
Software	Network Management Software	0.732	0.979	0.247	NA
Software Development	Software Systems	0.104	0.340	0.236	NA
Software	Platform as a Service	0.131	0.362	0.231	Third-party cloud computing model
Tablets	Tablets	0.057	0.277	0.219	NA
Data Center and IT Infra.	Data Integration	0.679	0.894	0.214	NA
Data Center and IT Infra.	Network Management	0.130	0.340	0.210	NA
CRM and Sales Related	Web Content	0.115	0.319	0.204	Website content management systems
Software	Accounting Software	0.414	0.426	0.011	Automates financial management
Server	Server	0.725	0.723	-0.001	NA
Server Operating System	Other System Manuf	0.980	0.936	-0.043	NA
Software	Application Server Software	0.619	0.511	-0.108	Interface between database servers and web servers
Router	Primary Router Manufacturer	0.867	0.745	-0.122	NA
Software	Network Firewall	0.792	0.617	-0.175	NA
Lan Switch	Primary Switch Manufacturer	0.608	0.362	-0.247	NA

Table II: Summary statistics for PPP estimation models. Sample observations have more than one PPP loan as well as nonmissing values of bank controls and FSS. Financial stock variables are measured as the average quarterly balance over quarters in 2019, branches are measured 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
SBA7a	0.31	0	0.46	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 III: 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 one 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. Columns 7 and 8 restrict the sample to participation and intensity of PPP loans for Phase 1 of the PPP program (through April 16). Columns 9 and 10 restrict the sample to participation and intensity of PPP loans made between April 24 and June 30, 2020.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Q2	Q2	Q2	Q2	Q2	Q2	Phase1	Phase1	Phase2	Phase2
VARIABLES	Pr(PPP>0)	Pr(PPP>0)	Ln(Loan)	Ln(Loan)	Ln(Loan<1m)	Ln(Loan≥1m)	Pr(PPP>0)	Ln(Loan)	Pr(PPP>0)	Ln(Loan)
FSS	0.0570***	-0.0155	0.101***	0.00879***	0.00794***	0.0188***	-0.00886	0.00749***	-0.0126	0.00779***
	(0.00887)	(0.00991)	(0.00313)	(0.00267)	(0.00255)	(0.00268)	(0.00953)	(0.00289)	(0.00839)	(0.00278)
SBA7a		1.940***		0.355***	0.323***	0.371***	1.827***	0.440***	1.191***	0.205***
		(0.307)		(0.0375)	(0.0357)	(0.0390)	(0.262)	(0.0401)	(0.176)	(0.0405)
$\text{Ln}(\text{Emp}_{t-2})$		0.0803		0.361***	0.346***	-0.0939	0.0630	0.332***	0.137	0.366***
		(0.209)		(0.0810)	(0.0801)	(0.0637)	(0.201)	(0.0768)	(0.177)	(0.0847)
$\text{Ln}(\text{CoreDep}_{t-2})$		1.391***		0.149	0.181	0.317*	1.352***	0.473**	0.840**	-0.00362
		(0.467)		(0.247)	(0.247)	(0.179)	(0.447)	(0.205)	(0.382)	(0.270)
$\text{Ln}(\text{Eq}_{t-2})$		0.0355		-0.274***	-0.232***	0.173**	0.129	-0.294***	-0.199	-0.171**
		(0.239)		(0.0816)	(0.0751)	(0.0729)	(0.220)	(0.0862)	(0.217)	(0.0788)
$\text{Ln}(\text{CI}_{t-2})$		0.222***		0.217***	0.186***	0.263***	0.301***	0.257***	0.192***	0.126***
		(0.0509)		(0.0228)	(0.0207)	(0.0224)	(0.0530)	(0.0268)	(0.0468)	(0.0213)
$\text{Ln}(\text{Branch}_{t-2})$		0.484***		0.00577	0.0674	-0.0600	0.421***	0.0126	0.162	0.110**
		(0.138)		(0.0518)	(0.0509)	(0.0385)	(0.129)	(0.0488)	(0.123)	(0.0542)
$\text{Ln}(\text{Commitment}_{t-2})$		0.517***		0.225***	0.236***	0.153***	0.516***	0.300***	0.414***	0.182***
		(0.0764)		(0.0370)	(0.0353)	(0.0329)	(0.0750)	(0.0408)	(0.0712)	(0.0358)
$\text{Ln}(\text{Asset}_{t-2})$		-2.144***		0.0220	-0.0638	-0.148	-2.215***	-0.436*	-1.248**	0.124
		(0.586)		(0.252)	(0.249)	(0.195)	(0.554)	(0.239)	(0.497)	(0.266)
PPP_Demand		-1.061		1.701***	-0.271	-1.938***	-0.648	0.598	6.582***	-0.605
		(1.279)		(0.452)	(0.382)	(0.373)	(1.190)	(0.464)	(2.206)	(0.452)
COVID_Exposure		1.282		-1.624***	-1.665***	-0.393	2.891*	-1.756***	1.014	-1.974***
		(1.690)		(0.500)	(0.453)	(0.519)	(1.558)	(0.562)	(1.674)	(0.491)
Constant	1.116***	3.563**	3.786***	-0.485	0.190	-6.558***	3.188*	-0.133	2.040	-0.271
	(0.129)	(1.785)	(0.0519)	(0.567)	(0.559)	(0.487)	(1.699)	(0.595)	(1.485)	(0.576)
Observations	3,384	3,384	2,961	2,961	2,961	2,961	3,384	2,859	3,384	2,872
R-squared			0.349	0.685	0.715	0.712		0.647		0.663

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

Table IV: 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.

VARIABLES	(1) County HHI	(2) County HHI	(3) County HHI	(4) State HHI	(5) State HHI	(6) State HHI
FSS	-0.00166***	-0.00406***	-0.00143**	-0.00190***	-0.00247***	-0.00247***
	(0.000421)	(0.00145)	(0.000624)	(0.000534)	(0.000643)	(0.000921)
SBA7a	-0.0197***	-0.0348*	-0.0105	-0.0276***	-0.0233**	-0.0324**
	(0.00694)	(0.0203)	(0.0109)	(0.00842)	(0.00966)	(0.0150)
Ln(Emp_{t-2})	-0.0357***	-0.0520**	-0.0370**	-0.0523***	-0.0452***	-0.0303
	(0.0110)	(0.0231)	(0.0152)	(0.0137)	(0.0155)	(0.0203)
Ln(CoreDep_{t-2})	0.211***	0.267***	0.0937**	0.204***	0.198***	0.0865
	(0.0221)	(0.0432)	(0.0378)	(0.0316)	(0.0343)	(0.0698)
Ln(Eq_{t-2})	0.0138	0.00809	0.00272	0.0254*	0.0198	0.00627
	(0.0147)	(0.0288)	(0.0246)	(0.0153)	(0.0165)	(0.0365)
Ln(CI_{t-2})	-0.0185***	-0.0333***	-0.0102	-0.0173***	-0.0173***	-0.00773
	(0.00431)	(0.00786)	(0.00806)	(0.00458)	(0.00501)	(0.0129)
Ln(Branch_{t-2})	0.0523***	0.0822***	0.0243**	0.0455***	0.0492***	0.0283*
	(0.00876)	(0.0165)	(0.0119)	(0.00959)	(0.0108)	(0.0152)
Ln(Commitment_{t-2})	-0.00300	0.00634	0.00891	-0.000998	0.00260	-0.00526
	(0.00665)	(0.0116)	(0.0101)	(0.00737)	(0.00804)	(0.0156)
Ln(Asset_{t-2})	-0.199***	-0.231***	-0.0713	-0.189***	-0.187***	-0.0516
	(0.0300)	(0.0611)	(0.0464)	(0.0372)	(0.0408)	(0.0730)
PPP_Demand	0.294***	0.297	0.796***	0.347***	0.280***	0.798**
	(0.0982)	(0.204)	(0.183)	(0.0992)	(0.106)	(0.314)
COVID_Exposure	-0.554***	-0.544**	0.0330	-0.148	-0.111	-0.150
	(0.104)	(0.215)	(0.198)	(0.104)	(0.119)	(0.203)
CountyHHI_Dep	0.547***		0.269***			
	(0.0136)		(0.0396)			
CountyCRA_HHI			0.541***			
			(0.0585)			
StateHHI_Dep				0.875***		0.399***
				(0.0226)		(0.0554)
StateCRA_HHI						0.533***
						(0.0516)
Constant	-0.0184	0.443**	-0.187	-0.0850	0.850***	-0.325
	(0.0915)	(0.184)	(0.137)	(0.106)	(0.114)	(0.233)
Observations	2,961	966	445	2,961	2,458	445
R-squared	0.533	0.143	0.804	0.425	0.078	0.768

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

Table V: Regressions of lender-level geographic PPP loan concentration using county shares. Regressions exclude banks above $10 billion in assets. FinTech is an indicator variable equal to 1 for firms identified in Erel and Liebersohn (2022) and zero otherwise. The variable bank95 are banks with FSS in the top five percent of all banks. 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.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Loan HHI	Loan HHI	Loan HHI	Loan HHI	Loan HHI	Loan HHI
bank95	-0.103***	-0.0797***	-0.0733***	-0.104***	-0.0763***	-0.0731***
	(0.0177)	(0.0177)	(0.0180)	(0.0177)	(0.0179)	(0.0181)
Fintech	-0.187***	-0.128***	-0.139***	-0.184***	-0.136***	-0.147***
	(0.0139)	(0.0158)	(0.0132)	(0.0142)	(0.0150)	(0.0142)
SBA7a	0.0132	0.0291**	0.0326**	0.0134	0.0308**	0.0332**
	(0.0134)	(0.0130)	(0.0131)	(0.0134)	(0.0130)	(0.0133)
Ln(PPPLoans)		-0.0758***	-0.265***		-0.0848***	-0.314**
		(0.00754)	(0.0542)		(0.00852)	(0.127)
$(\text{Ln(PPPLoans)})^2$			0.0121***			0.0155*
			(0.00318)			(0.00836)
Constant	0.246***	0.765***	1.486***	0.246***	0.825***	1.662***
	(0.0106)	(0.0537)	(0.222)	(0.0106)	(0.0602)	(0.477)
Observations	821	821	821	816	816	816
R-squared	0.054	0.141	0.148	0.052	0.138	0.141

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

Table VI: 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	-0.0205	0.00280***	0.00293***	0.00385	0.00261***	0.00319***
	(0.0294)	(0.000609)	(0.000611)	(0.0105)	(0.000563)	(0.000633)
SBA7a	0.533	0.0250***	0.0258***	0.555***	0.0159*	0.0130
	(0.768)	(0.00939)	(0.00940)	(0.172)	(0.00833)	(0.00901)
Ln(Emp_{t-2})	-0.0646	0.0291*	0.0295**	0.161	0.0408***	0.0371**
	(0.858)	(0.0149)	(0.0149)	(0.215)	(0.0155)	(0.0177)
Ln($CoreDep_{t-2}$)	-0.712	-0.228***	-0.226***	-0.889*	-0.187***	-0.190***
	(1.565)	(0.0317)	(0.0317)	(0.527)	(0.0379)	(0.0410)
Ln(Eq_{t-2})	0.217	0.00622	0.00739	-0.451*	-0.0118	0.00955
	(0.773)	(0.0191)	(0.0190)	(0.242)	(0.0157)	(0.0194)
Ln(CI_{t-2})	0.487***	0.0160***	0.0135**	0.437***	0.0119***	0.00748
	(0.114)	(0.00520)	(0.00538)	(0.0631)	(0.00456)	(0.00618)
Ln($Branch_{t-2}$)	0.181	-0.0707***	-0.0721***	0.111	-0.0429***	-0.0462***
	(0.678)	(0.0107)	(0.0107)	(0.131)	(0.0102)	(0.0120)
Ln($Commitment_{t-2}$)	0.782***	0.000582	-0.00430	0.273***	-0.00375	-0.0139
	(0.263)	(0.00832)	(0.00843)	(0.0925)	(0.00815)	(0.0103)
Ln($Asset_{t-2}$)	-0.0433	0.181***	0.184***	1.362**	0.165***	0.156***
	(2.024)	(0.0392)	(0.0391)	(0.659)	(0.0424)	(0.0462)
PPP_Demand	-3.945	-0.569***	-0.550***	1.242	-0.228**	-0.281**
	(2.989)	(0.123)	(0.122)	(1.344)	(0.106)	(0.122)
COVID_Exposure	-0.821	0.436***	0.449***	-1.374	0.116	0.202*
	(4.140)	(0.138)	(0.138)	(1.856)	(0.0936)	(0.109)
Constant	0.126	0.627***	0.620***	-7.860***	0.248**	0.379***
	(6.629)	(0.116)	(0.115)	(1.628)	(0.108)	(0.124)
Observations	2,961	2,961	2,928	2,961	2,961	2,453
R-squared		0.116	0.120		0.052	0.065

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

Table VII: 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	-0.0199	0.0181	-0.0161	-0.0509	0.00687	-0.00852	-0.00955
	(0.207)	(0.0582)	(0.0541)	(0.0581)	(0.0125)	(0.0157)	(0.0157)
FSS_Hard	-0.249**	0.0696**	0.0856***	0.0912***	-0.0170***	0.0298***	0.0330***
	(0.112)	(0.0309)	(0.0290)	(0.0292)	(0.00579)	(0.00746)	(0.00746)
FSS_Serv	-0.605	-0.208**	-0.244***	-0.0321	0.0267**	-0.0422**	-0.0406**
	(0.383)	(0.0810)	(0.0768)	(0.0824)	(0.0121)	(0.0203)	(0.0203)
FSS_Soft	0.0181	0.00844**	0.00777**	0.0146***	-0.00118	0.00173*	0.00155
	(0.0148)	(0.00416)	(0.00377)	(0.00386)	(0.000734)	(0.000982)	(0.000984)
SBA7a	1.997***	0.386***	0.348***	0.441***	-0.0195***	0.0248***	0.0257***
	(0.300)	(0.0379)	(0.0357)	(0.0394)	(0.00697)	(0.00939)	(0.00939)
$Ln(Emp_{t-2})$	0.0762	0.372***	0.355***	-0.0789	-0.0363***	0.0301**	0.0309**
	(0.198)	(0.0799)	(0.0790)	(0.0625)	(0.0111)	(0.0150)	(0.0150)
$Ln(CoreDep_{t-2})$	1.534***	0.168	0.195	0.340**	0.212***	-0.230***	-0.228***
	(0.419)	(0.243)	(0.242)	(0.172)	(0.0220)	(0.0316)	(0.0315)
$Ln(Eq_{t-2})$	0.0691	-0.261***	-0.219***	0.176**	0.0137	0.00617	0.00679
	(0.235)	(0.0820)	(0.0754)	(0.0728)	(0.0147)	(0.0191)	(0.0191)
$Ln(CI_{t-2})$	0.208***	0.210***	0.180***	0.253***	-0.0186***	0.0161***	0.0136**
	(0.0503)	(0.0225)	(0.0205)	(0.0219)	(0.00431)	(0.00521)	(0.00538)
$Ln(Branch_{t-2})$	0.475***	-0.00561	0.0567	-0.0764**	0.0524***	-0.0729***	-0.0747***
	(0.129)	(0.0519)	(0.0510)	(0.0387)	(0.00883)	(0.0107)	(0.0107)
$Ln(Commitment_{t-2})$	0.514***	0.221***	0.231***	0.149***	-0.00295	0.000588	-0.00421
	(0.0756)	(0.0370)	(0.0352)	(0.0325)	(0.00665)	(0.00831)	(0.00840)
$Ln(Asset_{t-2})$	-2.300***	-0.00354	-0.0853	-0.173	-0.200***	0.183***	0.187***
	(0.557)	(0.247)	(0.244)	(0.188)	(0.0300)	(0.0393)	(0.0391)
PPP_Demand	-0.932	1.755***	-0.226	-1.873***	0.294***	-0.573***	-0.553***
	(1.304)	(0.454)	(0.383)	(0.371)	(0.0985)	(0.124)	(0.123)
COVID_Exposure	2.037	-1.489***	-1.551***	-0.255	-0.548***	0.417***	0.425***
	(1.735)	(0.492)	(0.446)	(0.526)	(0.104)	(0.138)	(0.138)
CountyHHI_Dep					0.542***		
					(0.0139)		
Constant	3.799**	-0.544	0.112	-6.521***	0.00408	0.588***	0.579***
	(1.715)	(0.567)	(0.557)	(0.487)	(0.0922)	(0.116)	(0.116)
Observations	3,384	2,961	2,961	2,961	2,961	2,961	2,928
R-squared		0.687	0.718	0.716	0.534	0.120	0.126

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

Table VIII: 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, using banks in with at least one out-of-county loan.

	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	0.0172***	0.0171***	0.0201***	0.0255***	0.0258***	0.0171***
	(0.00372)	(0.00377)	(0.00279)	(0.00511)	(0.00516)	(0.00312)
SBA7a	0.476***	0.476***	0.315***	0.417***	0.418***	0.128***
	(0.0527)	(0.0533)	(0.0409)	(0.0722)	(0.0730)	(0.0414)
Ln(Emp_{t-2})	0.419***	0.421***	-0.0354	0.434***	0.447***	0.0771
	(0.0967)	(0.0982)	(0.0648)	(0.131)	(0.133)	(0.0746)
Ln($CoreDep_{t-2}$)	-0.550**	-0.555**	-0.0973	-1.052***	-1.046***	-0.329*
	(0.256)	(0.261)	(0.154)	(0.331)	(0.338)	(0.170)
Ln(Eq_{t-2})	-0.254**	-0.265**	0.234***	0.00360	-0.00789	0.319***
	(0.102)	(0.104)	(0.0694)	(0.144)	(0.145)	(0.0792)
Ln(CI_{t-2})	0.275***	0.266***	0.243***	0.286***	0.274***	0.203***
	(0.0288)	(0.0290)	(0.0204)	(0.0423)	(0.0425)	(0.0244)
Ln($Branch_{t-2}$)	-0.253***	-0.240***	-0.147***	-0.228***	-0.230***	-0.155***
	(0.0602)	(0.0616)	(0.0433)	(0.0859)	(0.0876)	(0.0525)
Ln($Commitment_{t-2}$)	0.164***	0.166***	0.0438	0.0481	0.0400	-0.0178
	(0.0468)	(0.0472)	(0.0317)	(0.0684)	(0.0691)	(0.0371)
Ln($Asset_{t-2}$)	0.591**	0.597**	0.0445	0.810**	0.820**	0.112
	(0.276)	(0.284)	(0.173)	(0.359)	(0.367)	(0.186)
PPP_Demand	-0.113	-0.572	-1.482***	-1.187	-1.118	-0.988**
	(0.560)	(0.577)	(0.368)	(0.854)	(0.862)	(0.390)
COVID_Exposure	1.550**	1.599**	0.215	-0.0252	0.0533	0.714
	(0.678)	(0.682)	(0.512)	(0.922)	(0.921)	(0.560)
Constant	-0.0730	0.127	-3.846***	0.0847	0.146	-2.317***
	(0.678)	(0.691)	(0.494)	(0.927)	(0.940)	(0.558)
Observations	2,928	2,928	2,928	2,453	2,453	2,453
R-squared	0.447	0.439	0.494	0.276	0.266	0.325

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

Table IX: 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	-0.00199	-0.0102**	-0.00841**	0.00904***	-0.000374	-0.00450	-0.00469	0.0112***
	(0.00266)	(0.00507)	(0.00384)	(0.00297)	(0.00425)	(0.00294)	(0.00287)	(0.00337)
SBA7a	0.340***	0.245***	0.239***	0.171***	-0.134**	0.365***	0.344***	0.395***
	(0.0405)	(0.0761)	(0.0601)	(0.0319)	(0.0611)	(0.0497)	(0.0467)	(0.0391)
$Ln(Emp_{t-2})$	0.187***	-0.196	-0.201	-0.112	-0.139	-0.0460	-0.0258	-0.353***
	(0.0706)	(0.149)	(0.159)	(0.0788)	(0.0851)	(0.105)	(0.109)	(0.0968)
$Ln(CoreDep_{t-2})$	0.793***				0.601***			
	(0.194)				(0.151)			
$Ln(Eq_{t-2})$	-0.308***	-0.275	-0.0691	-0.0349	-0.0507	-0.337***	-0.252***	-0.0179
	(0.0907)	(0.205)	(0.128)	(0.0978)	(0.107)	(0.0915)	(0.0807)	(0.0766)
$Ln(CI_{t-2})$	0.171***	0.0559	0.104*	0.150***	-0.0835***	0.158***	0.163***	0.217***
	(0.0244)	(0.0655)	(0.0560)	(0.0269)	(0.0281)	(0.0301)	(0.0266)	(0.0247)
$Ln(Branch_{t-2})$	0.226***				0.143***			
	(0.0538)				(0.0519)			
$Ln(Commitment_{t-2})$	0.225***	0.237***	0.195***	0.127**	-0.0395	0.283***	0.272***	0.219***
	(0.0335)	(0.0634)	(0.0502)	(0.0509)	(0.0416)	(0.0335)	(0.0335)	(0.0367)
$Ln(Asset_{t-2})$	-0.459**	0.0357	-0.174	-0.231*	-0.371*	-0.195	-0.293**	-0.129
	(0.221)	(0.290)	(0.225)	(0.130)	(0.211)	(0.153)	(0.144)	(0.124)
PPP_Demand	2.983***				1.532**			
	(0.519)				(0.675)			
COVID_Exposure	-2.234***				0.366			
	(0.759)				(1.151)			
$Ln(CountyDep_{t-2})$		0.478***	0.492***	0.181***				
		(0.0383)	(0.0383)	(0.0187)				
$Ln(CountyBr_{t-2})$		0.486***	0.506***	0.285***				
		(0.0560)	(0.0455)	(0.0278)				
$Ln(StateDep_{t-2})$						0.407***	0.403***	0.303***
						(0.0493)	(0.0505)	(0.0364)
$Ln(StateBr_{t-2})$						0.477***	0.510***	0.260***
						(0.0626)	(0.0627)	(0.0440)
Constant	-1.627***	-1.399	-0.974	-0.911*	0.556	1.027	1.453	-4.453***
	(0.564)	(1.580)	(1.660)	(0.496)	(0.717)	(0.885)	(0.903)	(0.671)
Observations	2,961	19,632	19,632	19,632	2,961	4,394	4,394	4,394
R-squared	0.663	0.670	0.741	0.622	0.019	0.704	0.728	0.705
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 X: Regressions of the in-area PPP loans on FSS and controls. In-area is defined based on the union of 2019 branch locations and 2019 SBA loans. Columns 1 through 3 use in-county lending. Columns 4 through 6 use in-state lending. SBA7a is a binary variable equal to one if the bank had at least one SBA loan in the county or state in 2019 and zero otherwise. One is added to logged variables so that they are well-defined. Errors are clustered at the bank-level for bank-geography OLS regressions.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Ln(Loan)	Ln(Loan<1m)	Ln(Loan>1m)	Ln(Loan)	Ln(Loan<1m)	Ln(Loan>1m)
FSS	-0.00715	-0.00983	0.00845***	-0.00452	-0.00452	0.00730*
	(0.00502)	(0.00656)	(0.00282)	(0.00393)	(0.00399)	(0.00380)
Ln(Emp_t-2)	-0.294**	-0.366*	-0.255***	-0.106	-0.101	-0.409***
	(0.130)	(0.197)	(0.0536)	(0.126)	(0.128)	(0.0813)
Ln(Eq_t-2)	-0.182	0.338	-0.0903	0.0187	0.0700	-0.0703
	(0.145)	(0.441)	(0.0811)	(0.330)	(0.331)	(0.0918)
Ln(CI_t-2)	0.0383	0.101	0.118***	0.189***	0.184***	0.205***
	(0.0451)	(0.0722)	(0.0223)	(0.0516)	(0.0509)	(0.0273)
Ln(Commitment_t-2)	0.210***	0.288***	0.153***	0.369***	0.358***	0.259***
	(0.0493)	(0.0689)	(0.0454)	(0.0484)	(0.0495)	(0.0373)
Ln(Asset_t-2)	0.111	-0.489	-0.0153	-0.560	-0.607	0.00813
	(0.169)	(0.575)	(0.104)	(0.473)	(0.475)	(0.137)
Ln(CountyDep_t-2)	0.334***	0.179***	0.0462***			
	(0.00560)	(0.00865)	(0.00381)			
Ln(CountyBr_t-2)	0.555***	0.711***	0.403***			
	(0.0436)	(0.0275)	(0.0235)			
Ln(StateDep_t-2)				0.144***	0.148***	0.0586***
				(0.0136)	(0.0137)	(0.00614)
Ln(StateBr_t-2)				0.552***	0.582***	0.394***
				(0.0372)	(0.0344)	(0.0239)
Ln(CountySBA7a)	0.265***	0.383***	0.184***			
	(0.0446)	(0.0531)	(0.0389)			
Ln(StateSBA7a)				0.316***	0.325***	0.236***
				(0.0435)	(0.0439)	(0.0274)
Observations	24,842	24,842	24,842	5,495	5,495	5,495
R-squared	0.841	0.692	0.587	0.683	0.704	0.684
County FE	YES	YES	YES	YES	YES	YES
State FE				YES	YES	YES

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

Table XI: 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
Accounting 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 Insurance Expenses	0.0076	0	0.1464	22125	3542	0.16

Table XII: 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Pr(PPP>0)	Ln(Loan)	County HHI	County HHI	Pr(PPP>0)	Ln(Loan)	County HHI	County HHI
Ln(OthNonIntX$_{t-2}$)	-0.913***	0.0823*	-0.0581***	-0.0902***				
	(0.175)	(0.0483)	(0.00944)	(0.0197)				
Ln(DataProc$_{t-2}$)					-0.129	0.0767***	-0.0149***	-0.0265**
					(0.118)	(0.0269)	(0.00499)	(0.0112)
SBA7a	2.028***	0.389***	-0.0165**	-0.0301	2.001***	0.372***	-0.0243***	-0.0496**
	(0.283)	(0.0374)	(0.00678)	(0.0192)	(0.327)	(0.0398)	(0.00739)	(0.0207)
Ln(Emp$_{t-2}$)	0.551**	0.298***	-0.00178	0.00702	-0.105	0.363***	-0.0386***	-0.0510**
	(0.223)	(0.0784)	(0.0116)	(0.0220)	(0.220)	(0.0825)	(0.0124)	(0.0247)
Ln(CoreDep$_{t-2}$)	0.919	-0.0445	0.162***	0.154***	1.736***	-0.0214	0.193***	0.207***
	(0.563)	(0.237)	(0.0214)	(0.0311)	(0.405)	(0.260)	(0.0257)	(0.0446)
Ln(Eq$_{t-2}$)	-0.176	-0.273***	0.00367	-0.0136	-0.0726	-0.280***	0.0218	0.0266
	(0.231)	(0.0807)	(0.0142)	(0.0265)	(0.249)	(0.0874)	(0.0159)	(0.0312)
Ln(CI$_{t-2}$)	0.261***	0.215***	-0.0191***	-0.0331***	0.264***	0.222***	-0.0192***	-0.0317***
	(0.0510)	(0.0216)	(0.00416)	(0.00711)	(0.0561)	(0.0234)	(0.00451)	(0.00770)
Ln(Branch$_{t-2}$)	0.360***	0.0787	0.0489***	0.0735***	0.409***	0.0140	0.0483***	0.0824***
	(0.119)	(0.0482)	(0.00799)	(0.0140)	(0.137)	(0.0541)	(0.00938)	(0.0166)
Ln(Commitment$_{t-2}$)	0.368***	0.204***	0.000153	0.00451	0.435***	0.209***	0.00182	0.0123
	(0.0772)	(0.0347)	(0.00607)	(0.00997)	(0.0822)	(0.0403)	(0.00676)	(0.0117)
Ln(Asset$_{t-2}$)	-0.838	0.185	-0.123***	-0.0724	-1.881***	0.155	-0.179***	-0.180***
	(0.732)	(0.254)	(0.0299)	(0.0515)	(0.565)	(0.268)	(0.0349)	(0.0672)
PPP_Demand	-1.373	1.872***	0.252***	0.275	-1.318	1.719***	0.278***	0.190
	(1.201)	(0.449)	(0.0964)	(0.187)	(1.323)	(0.493)	(0.104)	(0.195)
CountyHHI_Dep			0.551***				0.536***	
			(0.0134)				(0.0149)	
COVID_Exposure	-0.165	-1.754***	-0.590***	-0.674***	1.615	-1.318**	-0.601***	-0.765***
	(1.833)	(0.505)	(0.103)	(0.212)	(1.896)	(0.538)	(0.116)	(0.238)
Constant	1.215	-0.334	0.000147	0.477***	-0.838	-0.200	-0.0815	0.335*
	(1.472)	(0.530)	(0.0852)	(0.150)	(1.784)	(0.579)	(0.0994)	(0.192)
Observations	3,578	3,093	3,093	1,062	2,939	2,582	2,582	841
R-squared		0.681	0.526	0.162		0.651	0.503	0.132

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

Table XIII: 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	-0.0107	0.00835***	-0.00136***	-0.00388	0.0111***	-0.00168***
	(0.0101)	(0.00266)	(0.000420)	(0.0115)	(0.00297)	(0.000460)
Ln(OthNonIntX$_{t-2}$)	-1.052***	0.0468	-0.0503***			
	(0.174)	(0.0557)	(0.0105)			
Ln(DataProc_t-2)				-0.142	0.0719***	-0.0139***
				(0.126)	(0.0271)	(0.00491)
SBA7a	2.080***	0.385***	-0.0159**	2.024***	0.360***	-0.0222***
	(0.294)	(0.0381)	(0.00687)	(0.339)	(0.0405)	(0.00744)
Ln(Emp$_{t-2}$)	0.874***	0.338***	0.000765	0.149	0.360***	-0.0326***
	(0.237)	(0.0860)	(0.0127)	(0.241)	(0.0874)	(0.0125)
Ln(CoreDep$_{t-2}$)	1.169***	0.179	0.200***	1.490***	-0.0346	0.215***
	(0.411)	(0.244)	(0.0217)	(0.394)	(0.268)	(0.0251)
Ln(Eq$_{t-2}$)	-0.0619	-0.274***	0.00745	-0.0773	-0.304***	0.0199
	(0.234)	(0.0817)	(0.0147)	(0.270)	(0.0906)	(0.0164)
Ln(CI$_{t-2}$)	0.224***	0.209***	-0.0176***	0.238***	0.219***	-0.0176***
	(0.0525)	(0.0226)	(0.00425)	(0.0581)	(0.0242)	(0.00460)
Ln(Branch$_{t-2}$)	0.244*	0.00443	0.0461***	0.338**	-0.0413	0.0486***
	(0.134)	(0.0509)	(0.00867)	(0.156)	(0.0605)	(0.00984)
Ln(Commitment$_{t-2}$)	0.526***	0.221***	-0.00309	0.528***	0.224***	-0.00109
	(0.0764)	(0.0368)	(0.00654)	(0.0865)	(0.0418)	(0.00703)
Ln(Asset$_{t-2}$)	-1.432**	-0.0224	-0.165***	-1.915***	0.188	-0.198***
	(0.577)	(0.248)	(0.0308)	(0.552)	(0.272)	(0.0351)
PPP_Demand	-1.961	1.824***	0.237**	-1.538	1.935***	0.250**
	(1.269)	(0.452)	(0.0983)	(1.377)	(0.503)	(0.106)
CountyHHI_Dep			0.550***			0.535***
			(0.0135)			(0.0150)
COVID_Exposure	0.915	-1.412***	-0.585***	1.975	-1.171**	-0.615***
	(1.808)	(0.496)	(0.105)	(1.953)	(0.547)	(0.119)
Constant	3.530**	-0.441	-0.0113	1.262	-0.359	-0.0870
	(1.583)	(0.566)	(0.0907)	(1.896)	(0.613)	(0.103)
Observations	3,382	2,959	2,959	2,798	2,481	2,481
R-squared		0.687	0.537		0.655	0.516

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

Table XIV: 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 credit unions as the dependent variable, without and with county-level demographics, respectively. In calculating shares, PPP loans made by lenders not designated as banks, credit unions, or fintechs are excluded from the analysis (this excludes less than 1 percent of all PPP loans and less than 10 percent 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)
VARIABLES	% Out of County	% Out of County	% Fintech	% Fintech	% CU	% CU
Cnty Bank Tech	-0.00221***	-0.00287***	-0.000450**	-0.000517***	0.000284	0.000384
	(0.000820)	(0.000781)	(0.000182)	(0.000178)	(0.000253)	(0.000293)
Cnty Bank Size	0.0289***	0.0210***	0.00517***	0.00402***	0.000249	-0.000272
	(0.00450)	(0.00403)	(0.000807)	(0.000584)	(0.00132)	(0.00145)
Log(Branches)	-0.0834***	-0.193***	0.00129	-0.0102***	-0.0164***	-0.0197***
	(0.00938)	(0.0135)	(0.00195)	(0.00366)	(0.00297)	(0.00407)
Cnty Dep HHI	0.151***	0.116***	0.00801	0.00466	-0.0211***	-0.0220***
	(0.0407)	(0.0363)	(0.00609)	(0.00681)	(0.00633)	(0.00693)
Log(CU Branches)	-0.00145	-0.0246***	0.00233*	-0.000561	0.0474***	0.0456***
	(0.00603)	(0.00534)	(0.00129)	(0.00153)	(0.00449)	(0.00431)
Log(SBA Branches)	0.0180***	0.00208	0.00212	0.000323	-0.0105***	-0.00893***
	(0.00500)	(0.00555)	(0.00145)	(0.00179)	(0.00196)	(0.00154)
Log(Population)		0.161***		0.0144***		0.00207
		(0.0164)		(0.00315)		(0.00374)
% Urban		-0.000533*		6.37e-05		-2.38e-05
		(0.000279)		(7.79e-05)		(6.13e-05)
% age65		0.132		-0.0424**		0.0313
		(0.124)		(0.0207)		(0.0364)
2020Q2 Emp Gr		-0.000961		-0.000672*		0.000481
		(0.00108)		(0.000384)		(0.000415)
Observations	2,765	2,339	2,765	2,339	2,765	2,339
R-squared	0.283	0.406	0.475	0.485	0.507	0.523
State FE	YES	YES	YES	YES	YES	YES

Table XV: Difference in Differences Regressions of CRA Lending. Sample includes banks between $1 billion and $10 billion in assets that have year-on-year growth data from 2017-2020 inclusive (i.e. with 2017 growth as the change from 2016 to 2017) and are either above the 95th percentile FSS or below the 50th percentile FSS. Bank95 is a binary variable equal to one if above the 95th percentile FSS and zero otherwise. Sample excludes banks for which there are zero in-county or zero out-of-county loans for any year in the sample. Post is a binary variable equal to one in 2020 and zero otherwise. TotalLnGr is the difference in log annual CRA loans. TotalOutGr is the difference in log annual CRA loans made outside of a county in which the bank has a branch. TotalInGr is the difference in log annual CRA loans made inside of a county in which the bank has a branch. HHI Ratio is defined as the bank-year county HHI, calculated as the sum of squared shares of bank-year loans made in a county (with county shares calculated as loans in a county divided by total loans made in the bank-year). Columns 1 through 4 report results for a pooled sample for all years 2017-2020. Columns 5-10 also use 2020 data, but use bank averages over 2017-2019 for the pre-2020 period. Columns 9 and 10 include an interaction term between 2019 SBA lending and Post. Errors clustered at the bank level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	TotalLnGr	TotalOutGr	TotalInGr	HHI Ratio	TotalLnGr	TotalOutGr	TotalInGr	HHI Ratio	TotalLnGr	HHI Ratio
bank95*post	0.450**	0.456*	0.392**	-0.0683**	0.453**	0.461**	0.395**	-0.0758**	0.413**	-0.0696**
	(0.177)	(0.228)	(0.168)	(0.0315)	(0.177)	(0.228)	(0.168)	(0.0318)	(0.178)	(0.0328)
SBA7a*post									0.152	-0.0235
									(0.188)	(0.0370)
Observations	270	270	270	270	136	136	136	136	136	136
R-squared	0.729	0.513	0.746	0.850	0.801	0.682	0.821	0.886	0.803	0.886
YEAR FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

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

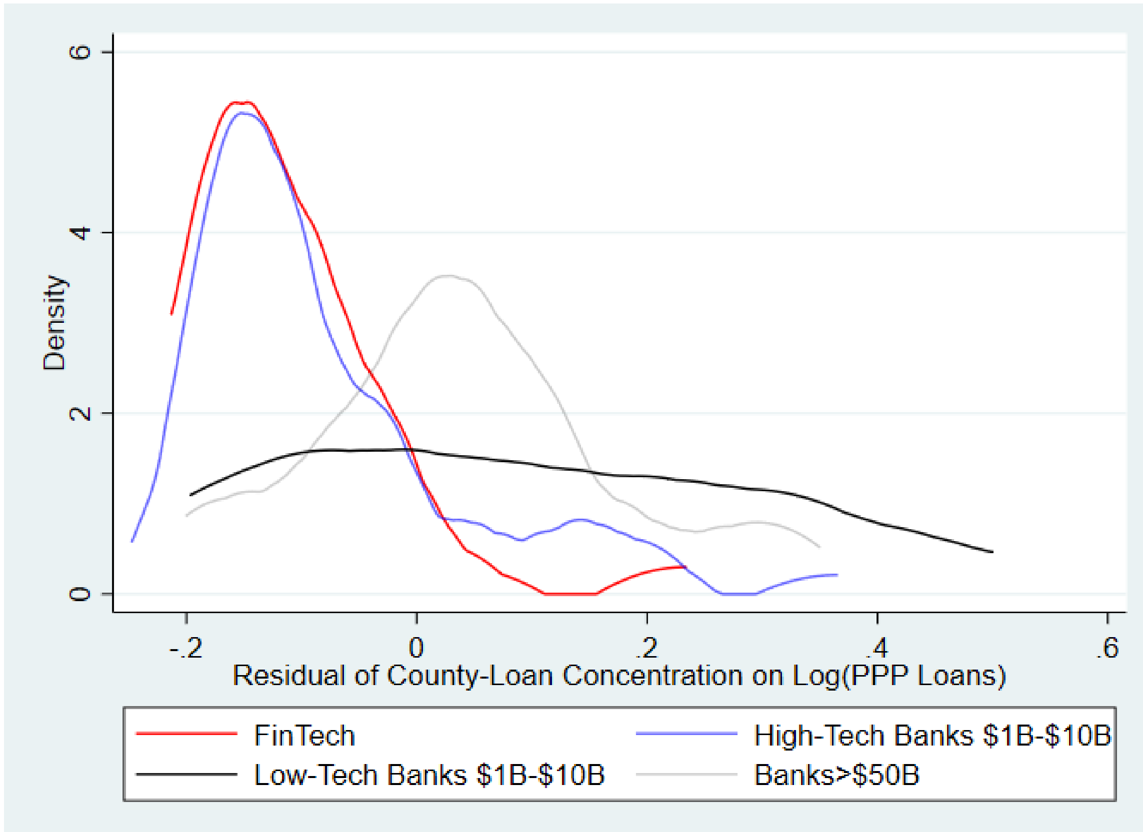


Figure I: Kernel density of PPP loan concentration by lender type. The figure plots kernel densities of residuals from a lender-level OLS regression of county-loan HHI on a quadratic expression of log PPP loans for lenders with at least 500 loans. Assets are as of year-end 2019. High-technology banks 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.

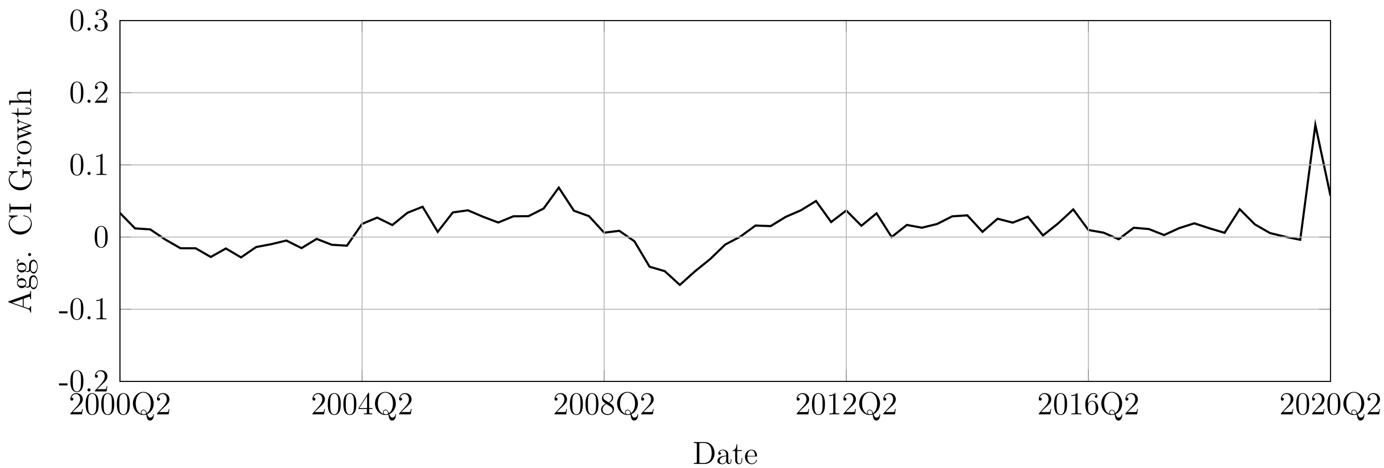


Figure II: Quarterly C&I Loan Growth, 2000Q2-2020Q2. Source: FDIC Quarterly Banking Profile.

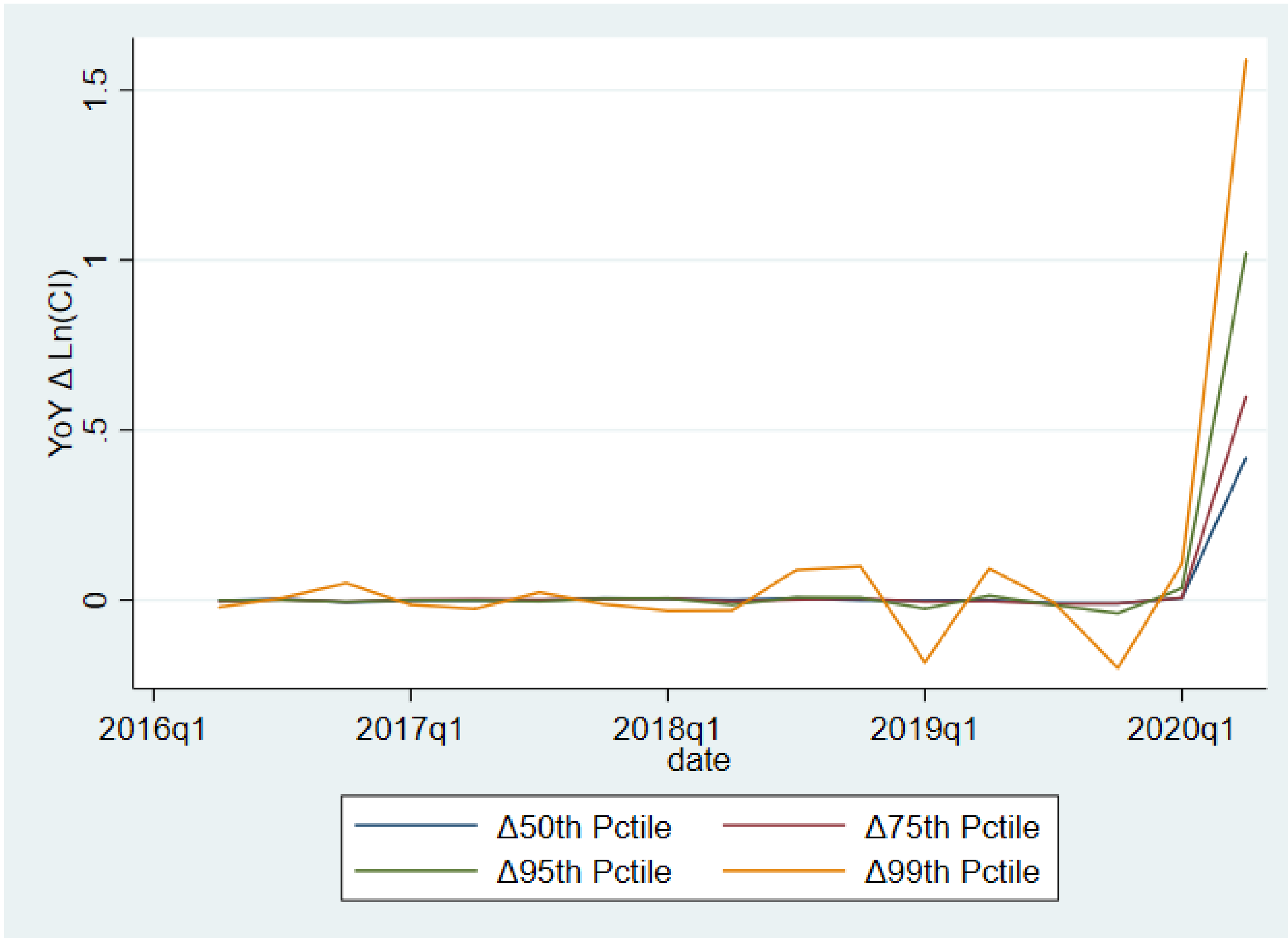


Figure III: C&I lending growth relative to lending growth one year prior (vertical axis), by quarter (horizontal axis), shaded lines by percentile of growth. Source: Call Reports.

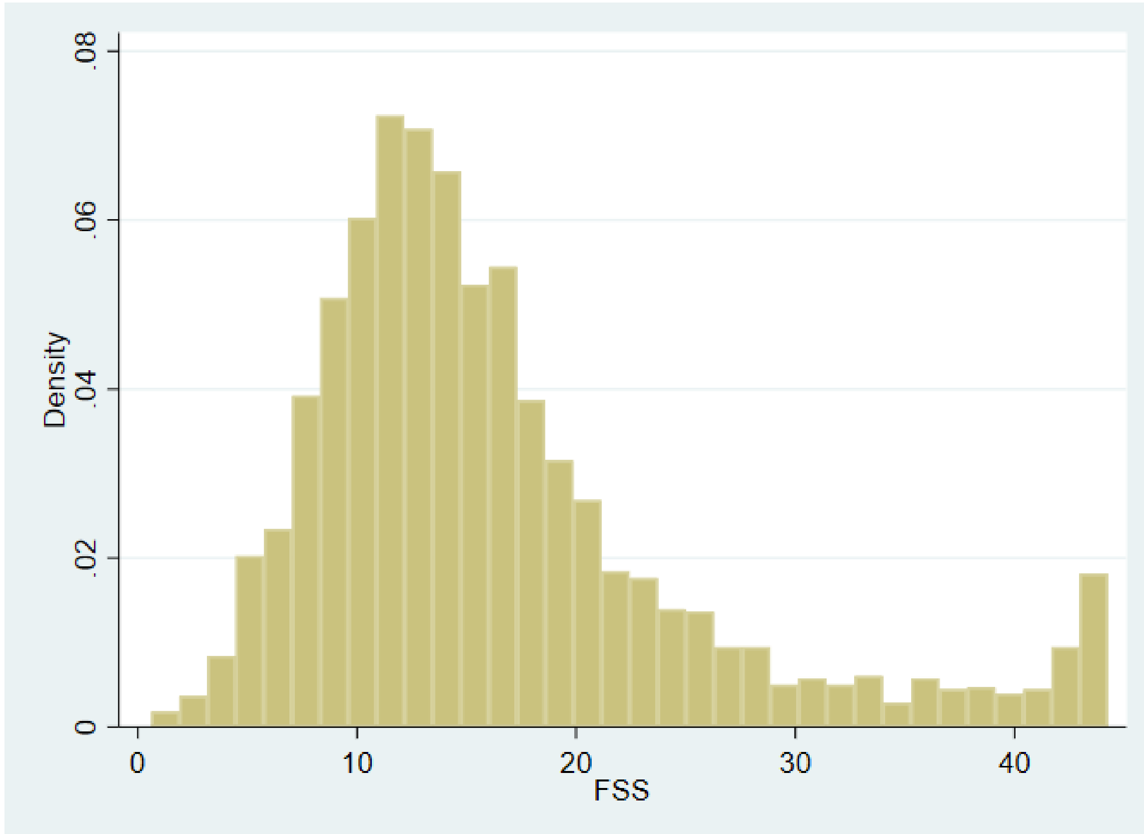
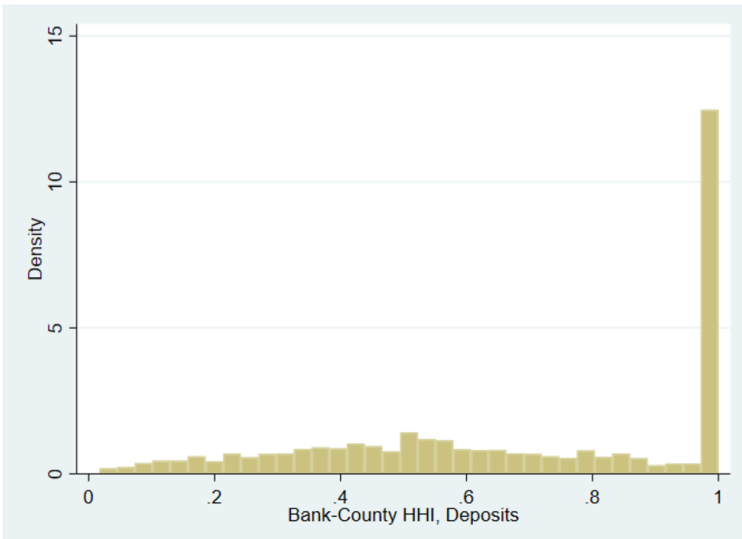
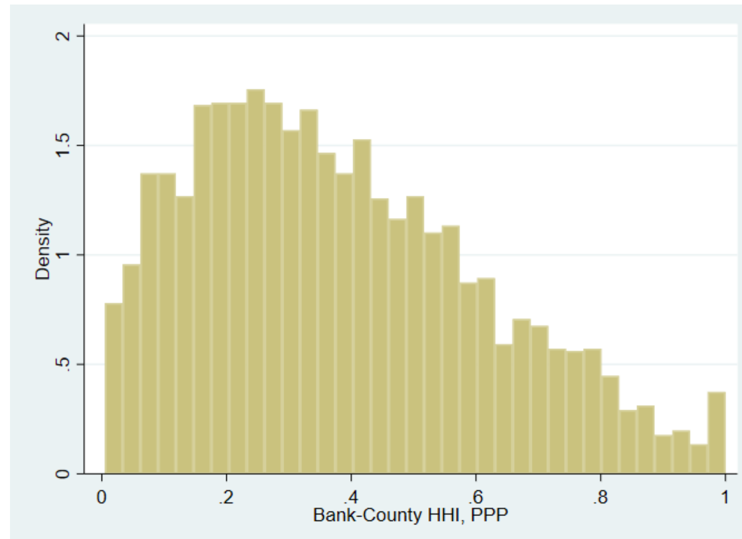


Figure IV: Histogram of Fintech Similarity Score (FSS) for subclass-level product installs for banks with PPP lending in 2020Q2.



(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.

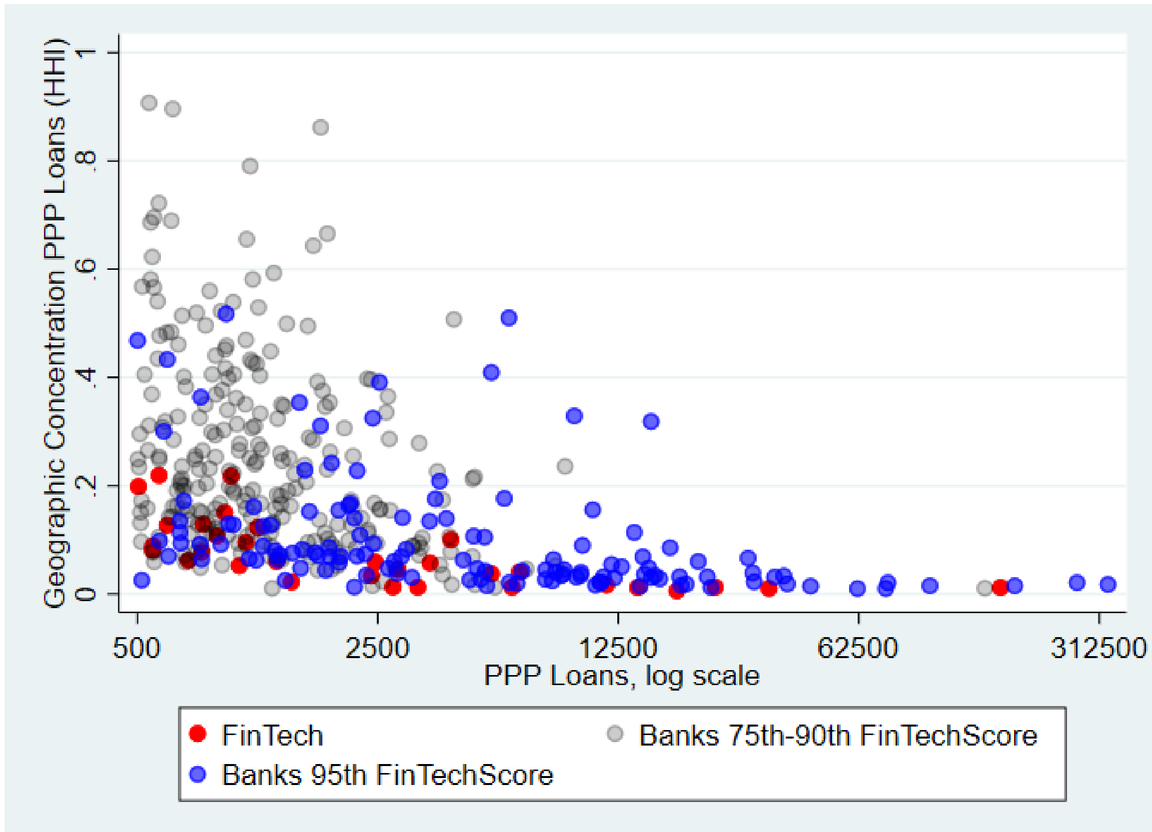


Figure VI: Scatter plot of log PPP loans (vertical axis) and geographic concentration of PPP loans (horizontal axis) shaded by lender type for nonbank fintech firms and banks according to FSS. Geographic concentration of PPP loans for each bank is measured as HHI of loans across counties.

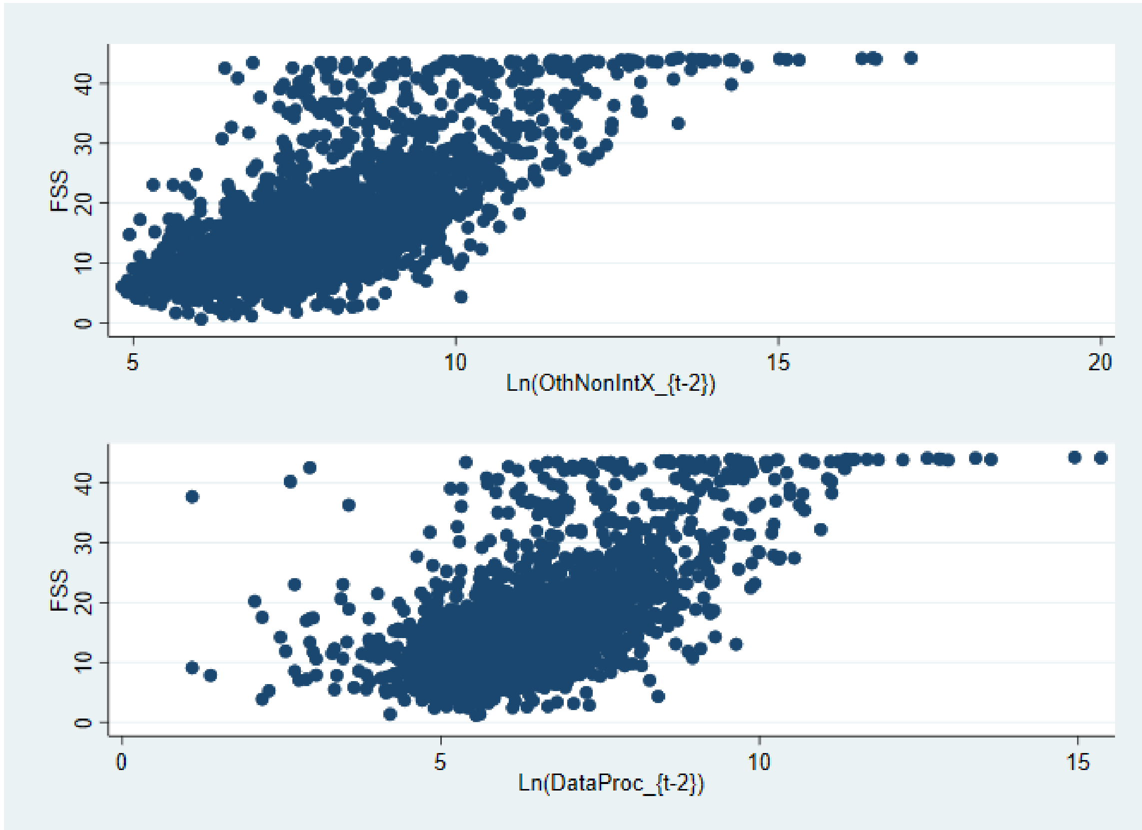
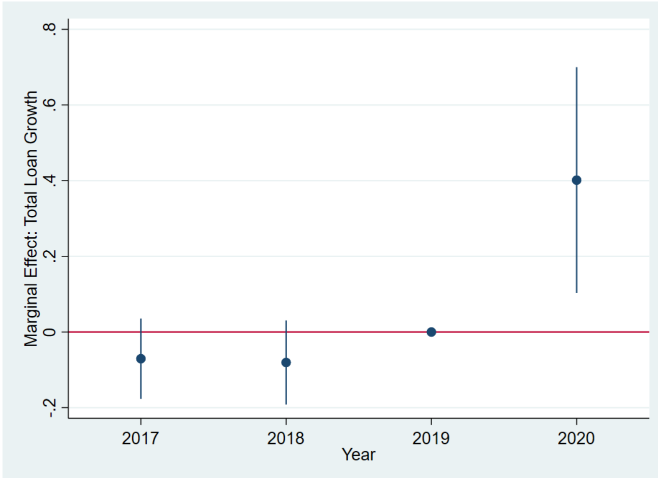
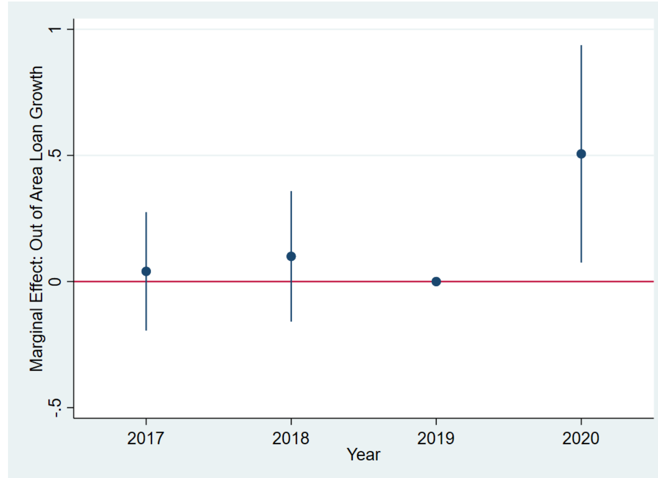


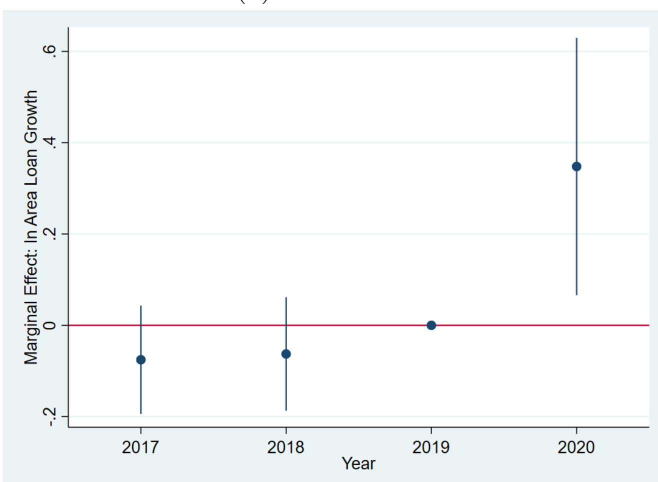
Figure VII: Plot of bank expenses and FSS for banks with PPP lending in 2020Q2. The top panel plots FSS and the log of other noninterest expense. The lower panel plots FSS and the log of data processing expense. Source: Call Reports, Aberdeen data.



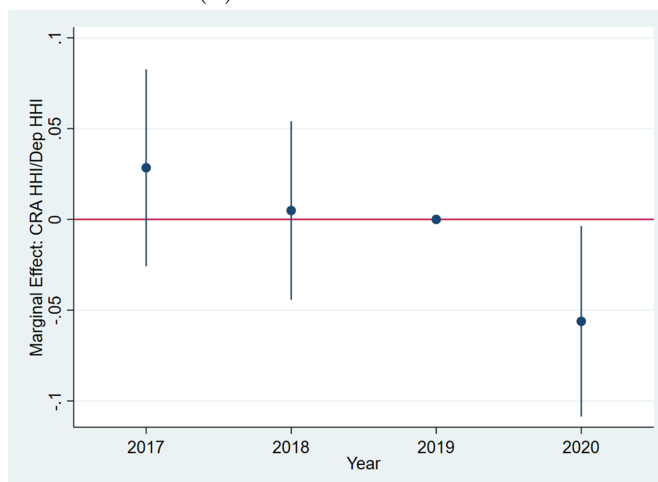
(a) Total Loans



(b) Out of Area Loans



(c) In Area Loans



(d) Loan Concentration

Figure VIII: Coefficients on interaction terms between a bank-level, high-technology, binary variable (95th percentile or higher in FSS for 2019) and yearly dummies. Lending data for 2016 to 2020 constructed using bank-county, annual loan originations (from public use CRA data) for small loans (under one million dollars) to businesses. Top left is total growth in loan originations. Growth of in- and out-of-area lending defined based on bank presence in a county from Summary of Deposits data. Bottom right is the ratio of bank loan concentration, normalized by bank deposit concentration, where concentration is measured by HHI calculated at the county level with number of CRA loans used to calculate loan concentration and total deposits in a county (from SOD) used to calculate deposit concentration.

Table A.XVI: Bank and fintech usage rates of technology subclasses (with examples), as well as the difference in usage of fintechs relative to banks. Use constitutes any establishment of a bank or fintech using any product in a subclass in 2019 as documented by Aberdeen. Rates report average usage across all banks and across all fintechs. Table rows are drawn from the set of product subclasses that are used by at least 5 percent of banks and 5 percent of fintechs and that are also used by at least 20 percent of either banks or fintechs. From those subclasses with substantive usage (67 out of 183 subclasses), the table presents the seven subclasses with the greatest use by fintechs relative to banks (top seven rows), the seven subclasses with the least use by fintechs relative to banks (bottom seven rows), and for seven intermediate subclasses. Product class and subclass definitions are from Aberdeen. Examples of subclass products report the manufacturer most often used by banks and the manufaturer most often used by fintechs (or the second-most used in cases where both banks and fintechs most often used the same manufacturer) as well as a product by that manufacturer (after the colon).

Class	Subclass	Bank	Fintech	Diff.	Example 1	Example 2
Software	Help Desk Management	0.058	0.745	0.686	BMC:RemdyHelpDsk	Zendesk:HELPDESK
Analytics	Business Intelligence (BI)	0.150	0.745	0.595	Platfora:Platfora	Tableau:Tableau Desk
Software	Collaborative/Integration Software	0.154	0.745	0.591	IBM:CICS	GitHub:COLLAB-SWFTR
Software Development	App Development	0.166	0.745	0.579	RequireJS:RequireJS	SAMSUNG:GALA
Software	CRM/SFA Software	0.116	0.681	0.565	Salesboom:SAAS-CRM	Gainsight:SAAS-CRM
Software	BI Software	0.143	0.681	0.538	Microsoft:BI	Heap Analyt:Heap
Desktop or Portable PC	Supply Chain Management Software	0.182	0.702	0.520	Google:Cloud	APACHE:Hive
Software	Network Management Software	0.732	0.979	0.247	OpenSource:nginx	GODADDY:GoDaddy DNS
Software Development	Software Systems	0.104	0.340	0.236	Microsoft:Microsoft Fr	Jetpack:JetPack
Software	Platform as a Service	0.131	0.362	0.231	Amazon:ElstcBnstlk	Salesforce:Force.com
Tablets	Tablets	0.057	0.277	0.219	APPLE:iPad	NA
Data Center and IT Infra.	Data Integration	0.679	0.894	0.214	Google:Google API	FACEBOOK:Facebook-Gra
Data Center and IT Infra.	Network Management	0.130	0.340	0.210	LoadDNS:LoadDNS	ns1:NSOne
CRM and Sales Related	Web Content	0.115	0.319	0.204	dotCMS:dotCMS	GHOST:Ghost
Software	Accounting Software	0.414	0.426	0.011	Jack-Henry:ACCTNG	Oracle:Fusion Cloud Fin.
Server	Server	0.725	0.723	-0.001	Micro-Focus:Service Mana	NGINX:Web Server
Server Operating System	Other System Manuf	0.980	0.936	-0.043	Microsoft:ASP.NET	OpenBSD:OS
Software	Application Server Software	0.619	0.511	-0.108	Apache-Soft:APP-SERVER	ampproject.:AMP
Router	Primary Router Manufacturer	0.867	0.745	-0.122	Cisco:1600	SMC:ROUTER
Software	Network Firewall	0.792	0.617	-0.175	FireBrick:Firewall	FireBrick:Firewall
Lan Switch	Primary Switch Manufacturer	0.608	0.362	-0.247	Cisco:CtlystSwtchs	3COM:SuperStack

Table A.XVII: Regressions of the geographic concentration of bank PPP loans on FSS and bank controls, including PPP loan volume. Table IV 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.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	County HHI	County HHI	County HHI	State HHI	State HHI	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)
Ln(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)
Ln(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)
Ln(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)
Ln(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)
Ln(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)
Ln(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)
Ln(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.XVIII: 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.

VARIABLES	(1) FSS	(2) Ln(OthNonIntX)	(3) Ln(DataProc)
SBA7a	0.623**	0.0545***	0.0561*
	(0.291)	(0.0151)	(0.0287)
Ln(Emp$_{t-2}$)	0.737*	0.684***	0.543***
	(0.421)	(0.0458)	(0.0441)
Ln(CoreDep$_{t-2}$)	-0.823	-0.302***	0.0389
	(1.038)	(0.0551)	(0.108)
Ln(Eq$_{t-2}$)	0.0319	-0.161***	0.0110
	(0.505)	(0.0329)	(0.0555)
Ln(CI$_{t-2}$)	0.233*	0.0280***	-0.000545
	(0.123)	(0.0106)	(0.0126)
Ln(Branch$_{t-2}$)	2.589***	-0.128***	-0.0710***
	(0.234)	(0.0191)	(0.0256)
Ln(Commitment$_{t-2}$)	0.0674	-0.0187	-0.00388
	(0.188)	(0.0244)	(0.0233)
Ln(Asset$_{t-2}$)	2.036	0.876***	0.377***
	(1.358)	(0.0980)	(0.137)
PPP_Demand	0.209	-1.180***	-1.013***
	(2.807)	(0.159)	(0.315)
COVID_Exposure	2.499	-0.643***	-1.064***
	(4.151)	(0.190)	(0.364)
Constant	-9.942***	-0.501	-1.198***
	(3.367)	(0.433)	(0.349)
Observations	2,961	3,093	2,582
R-squared	0.516	0.950	0.796

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

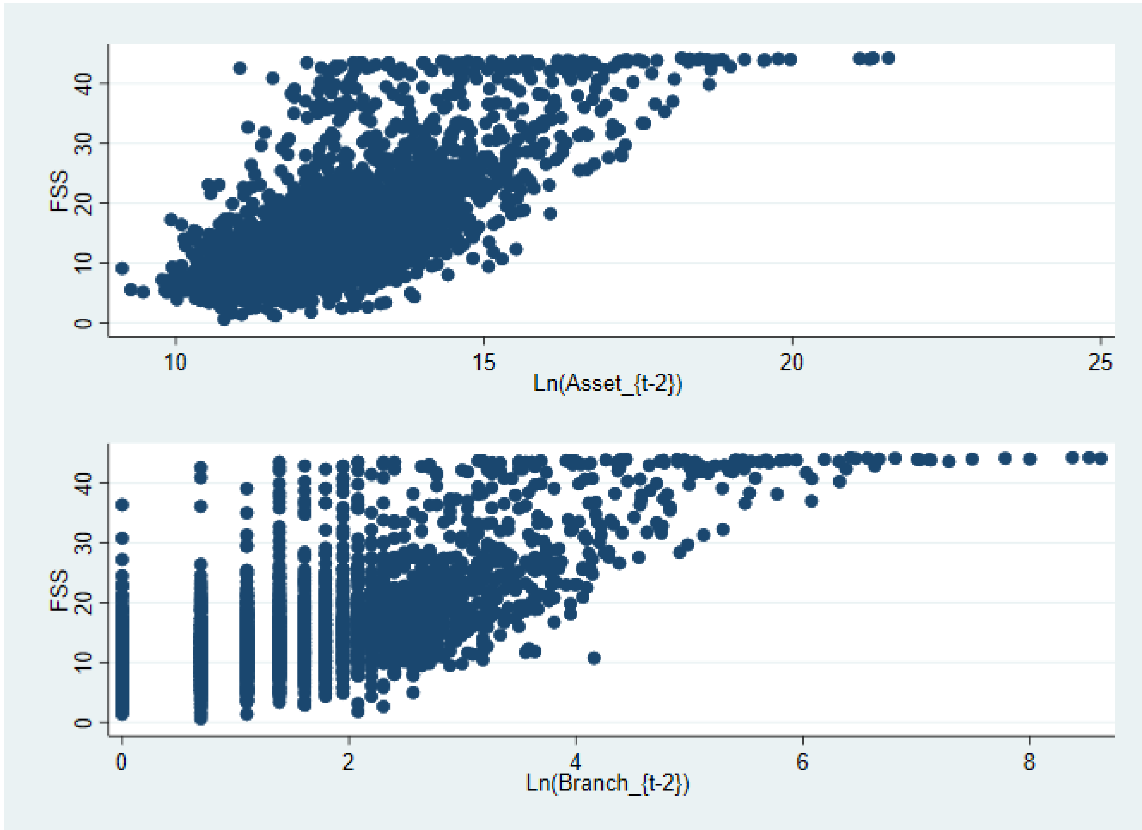


Figure A.IX: Plot of FSS (vertical axis) and bank characteristics (horizontal axis) for banks with PPP lending in 2020Q2. The top panel plots FSS and the log of total assets. The lower panel plots FSS and the log of number of branches. Source: Call Reports, Aberdeen data.