Does FinTech Substitute for Banks? Evidence from the Paycheck Protection Program*

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Abstract

New technology promises to expand the supply of financial services to borrowers poorly served by the banking system. Does it succeed? We study the response of FinTech to financial services demand created by the introduction of the Paycheck Protection Program (PPP). We find that FinTech is disproportionately used in ZIP codes with fewer bank branches, lower incomes, and a larger minority share of the population, as well as in industries with little ex ante small-business lending. FinTech's role in PPP provision is also greater in counties where the economic effects of the COVID-19 pandemic were more severe. Using the predicted responsiveness of traditional banks to the program in areas where they have branches as an instrument, we also show that only a small fraction of borrowers substituted to FinTech lenders when local traditional banks were not available.

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1 Introduction

The COVID-19 pandemic has created "a crisis like no other," with a projected global economic contraction of 4.9 percent in 2020.[1] It has induced tremendous stress on financial institutions, with an unprecedented demand for their services. Li, Strahan and Zhang (2020) show that, during the last three weeks of March 2020, commercial banks faced the largest increase in demand for credit ever observed. Among firms that needed emergency liquidity, small businesses have been hit the worst: According to a recent State of Small Business Report, nearly one third of small businesses have shut down; and many that still survive have faced important challenges with liquidity and revenue.[2] Our paper studies the role of FinTech in an important government program aimed at providing immediate relief to small businesses during this crisis.

As a response to the COVID-19 shock, the U.S. government created the Paycheck Protection Program (PPP), which offers guaranteed and potentially-forgivable small-businesses loans to "provide a direct incentive for small businesses to keep their workers on the payroll."[3] Although the program is administered by the Small Business Administration (SBA), approved financial institutions receive applications and distribute the funds, but do not bear credit risk from the loans. Traditional financial institutions (i.e., depository institutions), however, have been shown to be inefficient in their allocation of financial services across customers from different locations and demographics (Philippon, 2015), and, in the particular case of allocating PPP loans, have been heavily criticized by the popular media for favoring their relationship bor-

[1] World Economic Outlook Update, International Monetary Fund, June 2020.

[2] May 2020 State of Small Business Report by Facebook and Small Business Roundtable.

[3] PPP is an important part of the Coronavirus Aid, Relief, and Economic Security (CARES) Act: See https://www.sba.gov/funding-programs/loans/coronavirus-relief-options/paycheck-protection-program. See also Hamilton and Veuger (2020) for the importance of direct emergency loans in such unprecedented times.

rowers at the expense of smaller firms that were hit hardest by the pandemic.[4]

We also know that alternative sources of financial intermediation have been developing quickly (Mills, 2018). The role of Financial Technology (FinTech) has increased in different types of credit and other financial services, by not only unregulated non-banks but also by regulated banks.[5]

Our primary question is whether specialized FinTech lenders respond differently than traditional banks to the demand for PPP. This question speaks directly to the impact of including FinTech lenders when using banks as intermediaries to provide government services. Our setting allows us to compare responses of traditional banks and Fintech lenders, for the first time, to exactly the same type of financial service demanded. Furthermore, FinTechs are a growing share of the financial industry, so this study helps us understand how access to financial services changes as a result of their expansion, especially by people and in areas underserved by traditional banks.

We have three main findings. First, we show that during Phase 1 of the program, when traditional banks were most constrained, FinTech lenders provided more PPP loans to areas with a worse economic shock while traditional banks provided less. Second, we show that borrowers with less local access to the traditional banking system were more likely to get FinTech-enabled PPP loans. Specifically, comparing ZIP codes located in the same county, we find that a larger fraction of traditional bank PPP loans were originated to applicants in areas with more bank branches. Moreover, FinTech is disproportionately used in ZIP codes with lower incomes and a larger minority share of the population.

Relative to FinTechs, traditional banks also provided a higher fraction of PPP loans to firms in industries with stronger ties to the banking system, as proxied for

[4]E.g., "Banks Gave Richest Clients 'Concierge Treatment' for Pandemic Aid," NYT, April 2020.

[5]See, e.g., Buchak, Matvos, Piskorski and Seru (2018), Chernenko, Erel and Prilmeier (2019), Stulz (2019), Liebersohn (2020),and Gopal and Schnabl (2020).

by ex ante demand for SBA loans relative to new PPP demand. One-person firms, for example, are more likely to rely on FinTech loans. These findings support the view in the popular press that traditional banks base their PPP originations on past relationships and are geographically constrained by the location of their physical branches, unlike FinTech which is mainly online and where prior relationships are less relevant.

Finally, we study whether small businesses substitute to FinTech lenders when local banks are less responsive to their demand for PPP loans. If small businesses do not substitute between traditional banks and FinTechs, this may indicate that FinTechs supply financial services to a completely distinct market relative to the traditional banking system. To test whether substitution happens, we first create a bank-level measure of PPP responsiveness at the national level by calculating how many PPP loans each traditional bank originates per branch. Then, using the *ex ante* location of each bank's branches or deposits, we predict how much PPP origination we would expect based on the banks that happen to be located in each ZIP code, in an approach that is akin to a shift-share ("Bartik") design. Note that using national lending patterns to predict local bank responsiveness yields variation in traditional banks' PPP lending that is independent of the magnitude of the COVID-19 shock.

We find that, FinTech lenders originate more PPP loans per business in ZIP codes where our instrument predicts lower PPP lending by traditional banks. In other words, borrowers respond to a lack of bank PPP provision by somewhat substituting to these other types of financial institutions, despite the fact that many FinTech lenders were granted authorization only during the last few days of the Phase 1 of the PPP. But this substitution, which is significant statistically, is rather small economically. The number of FinTech loans that are made as a result of this substitution is only 0.3 percent of the decrease in traditional bank lending. Overall, these findings

show that FinTechs expanded the access to the PPP program but did not close the gap in financial services across regions where banks operate. But, the substitution is likely to be substantially larger in ZIP codes that are under-served by the traditional banking system as this estimate comes from ZIP codes where bank branches are located and the estimates are weighted by the number of branches per ZIP code.

The incentives in play for PPP loan origination are different from standard credit. Although technically termed "loans," PPP funds are forgivable in many circumstances and the lender does not bear any credit risk. Therefore, the differences in the response of FinTech and traditional banks in the PPP context may not map directly to the differences in standard credit provision. Our results speak to the differences between FinTechs and traditional banks' use of relationships to allocate credit and their use of new technology, but not to differences in credit evaluation and risk management. Nevertheless, the PPP program sheds light on how differences in technology and reliance on relationships between FinTech and traditional banks affect financial intermediation. Moreover, studying systematically the first government program, where traditional banks and FinTech lenders have been compared in terms of their responsiveness to the demand for exactly the same type of financial service, we have important policy implications. These implications speak to allowing (more) FinTech lenders in a timely manner to participate in any type of fully or partially-guaranteed government loan program (e.g., SBA 7a loans) to increase the efficiency of small-business lending not only during crises but also in non-crises periods.

The rest of the paper is organized as follows. Section 2 reviews the literature on FinTech lending. Section 3 describes the PPP, discusses the data collection process and presents summary statistics. In Section 4, we present our main results on geography of online and nonbank lending. Section 5 addresses whether ZIP codes with less bank branches had more PPP loans by FinTech lenders, controlling for local de-

mographics. In Section 6, we calculate predicted responsiveness of banks to the PPP and then test whether borrowers were more likely to get a FinTech-enabled loan if they are located in ZIP codes where local banks were unlikely to originate PPP loans. Section 7 concludes.

2 Literature Review

Our paper contributes to the nascent literature on the role of FinTech in providing financial services to firms or individuals. One paper that has studied differences between FinTech and traditional banks in credit provision, Chernenko et al. (2019), shows that FinTech provides relatively more credit to unprofitable businesses and that this is because they are subject to different regulation. In effect they find that the FinTech and traditional credit markets are highly segmented. We find that the FinTech-enabled PPP loans partially substituted for traditional loans.

Several other papers have studied the role of FinTech lending to firms. Davydiuk, Marchuk and Rosen (2020) study commercial lending by Business Development Companies (BDCs). Hanson, Shleifer, Stein and Vishny (2015), Cortes, Demyanyk, Li, Loutskina and Strahan (2020), and Gopal and Schnabl (2020) show how various nonbank lenders have been filling the gap when large commercial banks faced regulatory constraints and, therefore, had to pull back from lending to small firms.[6]

Although many purely online FinTech lenders started as peer-to-peer lenders extending only personal loans, they have also moved to direct small-business lending. As Stulz (2019) discusses, two well-known FinTech firms, LendingClub and Kabbage,

[6]There are also papers using Dealscan data on larger loans to study loans extended by or sold to nonbanks. For example, Carey, Post, and Sharpe (1998) focus on loans arranged by finance companies. Berlin, Nini and Yu (2018), Lim, Minton and Weisbach (2014), Nadauld and Weisbach (2012), Ivashina and Sun (2011), Massoud, Nandy, Saunders and Song (2011), and Jiang, Li and Shao (2010), Biswas, Ozkan and Yin (2018), Irani, Iyer, Meisenzahl and Peydro (2020) study participation by nonbanks in loans arranged and syndicated by banks.

make traditional small-business loans through a banking subsidiary or a funding bank partner. Buchak et al. (2018) show that there has been a dramatic growth in online FinTech lenders of mortgage loans post-financial crisis. FinTech banks have also been competing aggressively on the funding side of the financial institutions' balance sheet. Abrams (2019) points to the rapid growth in deposit contracts offered by online banks in the past decade: online banks now comprise four of the 30 largest banks by deposits, pay higher deposit rates, and have about the same amount of market power over their depositors as midsize banks do. Given the way the PPP program is structured, having an existing relationship with a bank, even through a simple commercial deposit account should matter.

Insufficient access to bank credit is one important reason for borrowers to bank with FinTech lenders (Cole, Cumming and Taylor (2019), Butler, Cornaggia and Gurun (2016), and Mills and Dang (2020)). Therefore, they are likely to serve the under-served and fill in gaps in lending, where traditional bank lending has contracted due to increased regulatory constraints during and after the financial crisis. They also offer convenience and faster processing through better technology (Buchak et al. (2018) and Fuster, Plosser, Schnabl and Vickery (2019)).[7] Carlin, Olafsson and Pagel (2020) find significant reductions in high-interest, unsecured debt and bank fees when individuals can get access to information about their bank balances and transactions more often. Therefore, they conclude that FinTech has significantly improved consumers' well-being. However, FinTech firms have limitations on what they can offer to customers. For example, Balyuk, Berger and Hackney (2020) show that FinTech lenders can substitute for hard-information-based lending by large out-

[7] There is also a growing literature on peer-to-peer personal loans that use FinTech, testing various predictions on lax screening/bottom fishing or cream skimming, comparing these loans with bank loans (see, e.g., Morse (2015) for a review; de Roure, Pelizzon and Thakor (2018), Di Maggio and Yao (2018), Tang (2019), and Vallee and Zeng (2019) for more recent papers).

of-market banks, but are less able to compensate for the loss of relationship-based lending from small, in-market banks.

Lastly, we also contribute to the literature on government interventions – especially, directed lending programs. Such programs can run in a form of a direct subsidy (e.g., Banerjee and Duflo (2014) using data from India) or an indirect subsidy as in a loan guarantee (e.g., Claire, Sraer and Thesmar (2010) using data from France). PPP is also a directed lending program, where the Small Business Administration offered guaranteed and potentially forgivable loans to small businesses. But borrowers apply for and receive loans through the system of financial institutions. Therefore, the role of these institutions in this process is essential. Some contemporaneous papers have also studied the PPP program. Cororaton and Rosen (2020) study public firms that got funding through the PPP and received significant media outrage as the program aimed to help small businesses. They document that only 13% of the eligible public firms, which is half of the public firms, end up participating. Using preliminary data, Granja, Makridis, Yannelis and Zwick (2020) examine whether areas that were more severely hit by the Covid pandemic, as measured by declines in hours worked or business shutdowns, end up getting more allocations. However, Barrios, Minnis, Minnis and Sijthoff (2020) develop a payroll-based framework and provide preliminary analyses that the state-level funds, which were granted till May 1st, were allocated as predicted by their framework. Moreover, Autor, Cho, Crane, Goldar, Lutz, Montes, Peterman, Ratner, Villar and Yildirmaz (2020) use administrative payroll data and find estimate that the PPP boosted employment at eligible firms by 2% to 4.5%. Bartik, Bertrand, Cullen, Glaeser, Luca and Stanton (2020) study the effects of PPP on small businesses using a representative national survey.[8] In this paper, we focus

[8]We also contribute to a broader literature studying the consequences of the COVID-19 crisis on financial and capital markets (see e.g., Green and Loualiche (2020), Fahlenbrach, Rageth and Stulz (2020), Pastor and Vorsatz (2020), Halling, Yu and Zechner (2020), and Falato, Goldstein and

on the differential effect of FinTech lenders in channeling PPP funds.

3 Payroll Protection Program and Data

The Paycheck Protection Program (PPP), which authorized up to $659 billion (in two Phases[9]) toward job retention by small businesses, is established by the CARES Act. This program provides loans to small businesses and eligible nonprofit organizations to pay up to eight weeks of payroll costs including benefits, interest on mortgages, rent, and utilities.[10] With about $525 billion approved — 5.2 million loans passed through 5,460 financial institutions— through final approval date of August 8, the PPP has been one of the largest economic stimulus programs in U.S. history. According to data reported by program participants, it has supported over 51 million jobs, clearly a majority of the small businesses' employment.

The program is administered by the Small Business Administration (SBA) but loans are allocated through eligible financial institutions. These eligible institutions include any SBA 7(a) lender, federally insured depository institutions or credit unions, or any other lender that is approved by the SBA and enrolled in the program. Lenders neither charge any fees nor ask for collateral to grant these small business loans. Loans issued prior to June 5 have a maturity of 2 years while the ones issued after June 5 have a maturity of 5 years. These PPP loans carry an interest rate of 1% but any loan payment is deferred for six months. Most importantly, the loans are fully forgiven if the funds are used for (at least 60%) payroll costs, interest on mortgages, rent, and utilities. The majority of loans granted were for less than $150,000, with the overall average loan size being $100,729.

Hortaçsu (2020)).

[9] $349 billion was distributed in Phase 1 over April 3-16, 2020.

[10] Tribal businesses, self-employed individuals, and independent contractors are also eligible if they meet the PPP's size standards.

Our main data source is the database of PPP loans released by the Small Business Administration (SBA) following an agreement between the Small Business Committee of the U.S. Senate and the Department of Treasury. Under the agreement, the SBA released loan-level data on all PPP loans. The data include some characteristics of borrowers and loans. For loans with a value above $150,000, borrower names are available, but the loan amounts are grouped into bins. For smaller loans, the exact dollar amount is available but not the borrower names. The borrower's industry information is available at the 6-digit NAICS level for all loans. The SBA also provided the names of the financial institutions (but no other identifiers) that facilitated the loan applications and distributions.[11]

We match this loan-level data to bank identifiers from the FFIEC using the lender names provided.[12] Most of the names are matched using automated name matching.[13] Lenders which we are not able to match automatically are a combination of non-bank lenders, banks that have duplicate names, and banks that have idiosyncratic names. We therefore hand-match all PPP lenders who originate over 750 PPP loans, classifying separately non-bank lenders and banks which do not have a unique match in the FFIEC database. This procedure allows us to match over 97% of all PPP loans in the sample. The remaining lenders are mostly small community banks with non-standard names. After matching the PPP data to the relevant financial institutions, we match these to institutional information for lenders that are deposit-taking banks. We ob-

[11] News reports have raised concerns about errors in some loans' data fields, especially free-form text fields and information about borrower demographics (Yanofsky, 2020). Our findings do not rely on borrowers' specific address or demographic information. Insofar as there are mistakes in ZIP codes, this would create measurement error in our dependent variables and would not bias the results.

[12] Specifically, we use the Attributes File from the end of June, 2020.

[13] We start by searching for exact, unique name matches between the files. For unmatched lenders, we try searching for common variants of their names, such as "N.A." in place of "National Association." PPP lenders whose names match multiple banks are matched to the bank with more branches. Names which remain unmatched are then matched by hand.

tain bank-level characteristics, including bank size, from June 2020 Call reports and data on the number of commercial bank branches by ZIP code from the 2018 FDIC Summary of Deposits database. Then we classify lenders into three categories: Large banks (with assets above $20bn), small banks and credit unions (with assets below $20bn), and FinTech lenders. In most of our analyses, we compare depository financial institutions (including savings institutions and credit unions), henceforth referred to as traditional banks, with FinTech lenders. Note that we treat any unclassified lender as a traditional bank.

We identified Fintech lenders as any unregulated nonbank lender that participated in the program as well as any regulated online direct bank. Specifically, nonbank lenders are non-depository financial institutions, like Kabbage, that generally rely on FinTech in their lending.[14] These nonbank lenders are not subject to typical bank regulation as they are not financed by deposits. Online banks, however, are regulated deposit-taking banks but with one administrative branch only. They also rely heavily on FinTech for both their lending and deposit taking. Therefore, we classify banks in our sample as online banks if they have one branch only but extended more than 500 PPP loans per branch to exclude small traditional community banks with single branches.[15] To this sample, we also added a few banks with more than one branch, as identified by Abrams (2019) as online banks. A few examples of these additions are Axos Bank, Capital One Bank, and the TIAA Bank. A full list of our FinTech lenders is provided in the Appendix B. We present results for online banks and nonbank lenders combined as FinTechs, but, in the Appendix Table A3, we also provide our main table with separate columns for these subgroups of institutions since

[14]Some nonbank lenders in the sample may not necessarily be traditional FinTechs (such as Business Development Corporations), but most are.

[15]In Appendix Table A2, we also provide our main table using a smaller subset of online banks as robustness. See the Appendix for the list of these FinTech lenders.

their regulatory treatment is different.

One interesting observation is that two one-branch community banks (Cross River bank and Celtic Bank) partnered heavily with FinTech firms and extended almost 350,000 PPP loans in total. These banks are classified as online banks in our sample. Kabbage, which is a nonbank lender, extended about 200,000 loans, making it the forth largest lender in terms of the number of PPP loans granted. We have three FinTech lenders in top five and four FinTech lenders in top ten PPP lenders by loan count.

Many of our analyses will be at the ZIP code level, in which we aggregate PPP lending based on the borrower's ZIP code. Unless otherwise specified, all estimates and summary statistics are weighted by the number of PPP loans per ZIP code. We measure the fraction of nonbank, online, and bank/credit union lending by ZIP code for borrowers whose type we have classified.[16]

We match this data to demographic information from the 2000 Decennial Census and the 2014-2018 American Community Survey (ACS) (Manson, Schroeder, Van Riper and Ruggles, 2017). From the Decennial Census, we measure the fraction of the population that is white. From the ACS, we measure total population, median household income, and travel time to work. We recode travel time to create an indicator that measures the fraction of households that report a travel time of over 45 minutes. Census variables are measured by ZIP Code Tabulation Area which we match to ZIP codes. To measure the economic characteristics of firms —i.e., the number and size of establishments— in each ZIP code, we use data from ZIP Business Patterns 2017 data. The average size of establishments is calculated as the total employment divided by the number of establishments in each ZIP code.

[16]Bank lending measured at the ZIP code level includes lending by credit unions, which are also depository institutions like commercial banks.

We measure the magnitude of the economic shock by county using data from the Opportunity Insights *Track the Recovery* web site (Chetty, Friedman, Hendren and Stepner, 2020). We focus on two main measures. First, we measure the four-week change in unemployment claims by county as of April 11, 2020. This measure covers the last week before unemployment started rising until the peak level of unemployment claims nationally. Second, we measure the average of the daily count of COVID cases by county in March per 100 people. See Chetty et al. (2020) for more details on these measures.

Summary Statistics by ZIP codes, weighted by PPP loans, are shown in Table 1.[17] Since we do not have loan amounts for all types of loans — only those with a value below $150,000 — our analysis focuses on the number of PPP loans rather than on their dollar amount.[18] However, in these types of direct government subsidies, it is at least as important to understand how many firms ended up benefiting from the loan program as the average value of the loan granted. 7% and 10% of all PPP loans were processed by nonbank lenders and online banks, respectively. Mean (median) ZIP code had 629 (515) PPP loans. In these ZIP codes, median income is about $64,000, only 14% of the population commute at least 45 minutes per day to work, and 80% of the population is white. In a typical ZIP code with PPP loans, there are 9.4 bank branches but with a standard deviation of 7.2 branches. Also, note that bank branch summary statistics are shown only for ZIP codes with a non-zero number of branches. A given ZIP code in our sample has 924 establishments and a total population of 13,736, on average. These areas also had 0.02% March COVID case rate and 3.35% unemployment growth.[19]

[17] See Table A1 for unweighted statistics.

[18] On average, FinTech lenders originate smaller loans than traditional banks do. The average loan size is 5 for FinTech lenders while it is 12 for traditional banks, as measured by self-reported jobs retained by the borrowers.

[19] Unemployment rates, which we can measure only at the county level, are not available every-

4 The Geography of Online and Nonbank Lending

Figure 1 shows the number of PPP loans by lender type between April 3, when the first Phase of the PPP started, and August 8, when the second Phase of the PPP ends. The X-axis of this figure shows the approval date and the Y-axis shows the number of PPP loans approved on each date by lender type. There is a gap between April 16, when PPP Phase 1 ended, and April 27, when Phase 2 began. Most of the PPP lending occurred in Phase 1 and in the beginning of Phase 2.

Media reporting during PPP Phase 1 suggested that smaller banks were better able to process PPP loans than larger banks. The evidence in the upper panel of this figure supports this view: During the initial weeks of PPP Phase 1, there were significantly more PPP loans arranged by small banks than by large ones.[20] The difference shrank towards the end of Phase 1, and by late Phase 2, large banks were responsible for more PPP lending than small banks were.

FinTech lenders were responsible for about 16% of PPP loans overall, with their share sharply increasing in Phase 2 of the program. The right panel of Figure 1 presents the FinTech fraction of total weekly average for PPP loans. The share of loans from FinTech institutions started increasing during the last few days of the Phase 1 and significantly accelerated during Phase 2, reaching to majority of overall lending. It is important to note here that many of the important FinTech participants got approved only during the last few days of the Phase 1, likely reducing the total number of PPP loans they could extend till the program expired.

Before we present the geographic distribution of PPP loans by traditional and Fin-

where.

[20] We believe that the unmatched banks in our sample are more likely to be credit unions and community banks than larger national banks, because community banks have names which are more difficult to match unambiguously (e.g., "First Bank" and "Farmers and Merchants Bank" each refer to many possible banks). Therefore, the difference between small and large banks may actually be understated in this figure.

tech lenders, we compare our measure of FinTech lending to an independent measure of interest in online PPP lending based on Google searches for online PPP lenders. Specifically, we use Google Trends to calculate, at the state level, variation across states in searches for the phrase "apply for ppp loan online" from March 1, 2020 to August 8, 2020. States with few searches are excluded from the Google Trends data.[21] Figure 2 shows the relationship between Google searches for online lending and our measure of actual PPP loans, with missing states located at zero. The relationship is positive and statistically significant whether or not we include states that have too few searches to include.

Next, we turn to the geographic distribution of relative PPP loan provision by FinTech lenders. The specifications in Table 2 explore the geographic correlates of PPP loan provision. Our first question is whether FinTech PPP loans flowed unconditionally to the areas that needed it most in both periods, and PPP lending is different for traditional banks versus FinTech financial institutions. To measure which areas were most in need of PPP loans, we use county-level variables collected by Chetty et al. (2020): the increase in unemployment claims rate between the months of March and April and the average COVID-19 case rate per 100 people in March. Our other variables are measured at the ZIP code level. We control for the log number of establishments by ZIP code to avoid a mechanical relationship between the number of establishments and the number of loans. Regressions are run at the ZIP code-level and estimates are weighted by total PPP loans by ZIP code. Robust standard errors are reported. Our dependent variable is the log of total PPP loans by traditional banks vs. FinTech lenders.

During Phase 1, traditional banks did not provide PPP financing to the regions

[21] The top state for online searches is Georgia. The largest nonbank FinTech lender in the sample is Kabbage, Inc., which is based in Atlanta.

with higher case rates or higher unemployment, as already found by Granja et al. (2020). In fact, traditional banks provided *fewer* PPP loans to counties which needed it more, along both measures (see Column (1) of Table 2). By contrast, FinTech loans did flow to areas with a worse COVID shock and a worse economic shock, despite the fact that majority of them got approval in the last few days of Phase 1 (see Column (2)). The difference between FinTechs and traditional banks is also economically meaningful in Phase 1. According to the coefficients in Column (1), each additional COVID case per 100 people was associated with 4 log-points less PPP lending from traditional banks and nearly 1 log-point more lending from FinTechs. One more percentage point increase in unemployment was associated with 0.07 log points less traditional bank lending and 0.07 log points more FinTech lending. We also focus, in Columns (3)-(4), on the dates of April 12-16 — when most FinTech lenders were already approved — and find a similar pattern as in the entirety of Phase 1.

During Phase 2, as shown in the last two columns of Table 2, PPP loans flowed towards areas that needed more assistance both from traditional banks and from online banks/online lenders. However, even then, FinTechs were more responsive to financial need than traditional banks were. The coefficient on the average case rate is more than ten times larger for FinTech loans than bank loans. During Phase 2, each additional COVID case per 100 people was associated with 5 log points more FinTech loans and 0.3 log points more loans from traditional banks. Supporting the widely-reported problems with banks' ability to provide PPP loans to areas that needed it during Phase 1 of the program, our findings seem to indicate that FinTech lenders were better able to respond to local demand.

Figure 3 is a county-level graph showing the fraction of PPP loans coming from each type of institution for the entire United States. Here, we consider a combination of Phase 1 and Phase 2 loans. There are clear patterns visible in this figure. Major

metropolitan areas, such Atlanta, Miami, Houston and Chicago, as well as both coasts, have a high fraction of their PPP loans originated by FinTech lenders. Urban parts of New Mexico, Colorado and Arizona also have significant FinTech PPP loan origination.

At a descriptive level, the national data on the FinTech PPP lending suggest that these sorts of loans are most common in areas that are already well-served by the banking system: coasts and major metro areas. However, would these borrowing patterns be similar at a more local level? To build intuition for these results, we consider the geography of lending by online banks and nonbanks in the city of Chicago.

Figure 4 shows the distribution of PPP loans for ZIP codes in Cook County, which includes most of the Chicago metro population. We are interested in understanding the distribution of FinTech loans in relation to demographic differences in ZIP codes within the metropolitan area. As shown in the left panel of this figure, Cook County is characterized by large differences in income by ZIP code. The North Shore is high-income and also mostly white, as are the western parts of Cook County. South Chicago has lower median incomes. Differences in income are sharp across neighborhood boundaries.

These differences manifest themselves in differences in the proportion of PPP loans that come from FinTech lenders as opposed to from traditional banks and credit unions. The right panel of Figure 4 shows the fraction of PPP loans which we classify as coming from FinTech lenders. Businesses in the richer ZIP codes of Chicago mostly get their loans from traditional banks and credit unions, whereas the lower-income areas get a higher fraction of their loans from FinTech-focused online banks and nonbanks. We have created similar maps for other major metro areas and found similar patterns. Moreover, this relation between online/nonbank lending and ZIP demographics is significant using linear regressions as well.

One possible reason for local differences in FinTech PPP lending by ZIP code is the variation in the location of traditional bank branches, a topic we now turn to. ZIP codes with more bank branches are known to have more competitive banking markets and hence better credit access. The relationship between bank branches and FinTech online and nonbank lending is shown in Figure 5, which is a binscatter plot. The left panel of this figure, labeled "National", uses pooled ZIP code data from the entire country. On the X axis, we show the average (log) bank branches per ZIP code, where ZIP codes are grouped into vintiles and the logarithms are in base-10 to make interpretation simpler. The Y axis shows the fraction of Fintech PPP loans for each vintile. Based on the national patterns Figure 3, we should not be surprised to see that regions with more bank branches also had a higher share of Fintech lending. Looking across regions, relationship between bank branches and FinTech lending is generally upward-sloping (although it is not perfectly linear).

But when we look within-county, these patterns are reversed: ZIP codes with fewer branches have a higher fraction of FinTech loans. The right panel of Figure 5 conditions on county fixed effects and hence uses only *within*-county variation in bank branches by ZIP code. Here, there is a clear negative relationship between PPP lending and the fraction of FinTech loans. In other words, although online banks and nonbank lenders have a larger presence in parts of the country with more traditional banking, they disproportionately serve under-resourced areas when we look *within* a county.

We next turn to linear regressions to quantify this evidence and to distinguish between the separate effects of bank branch location and demographic differences in loan demand.

5 Branch Distance and FinTech Lending

Borrowers in ZIP codes with more bank branches were less likely to get a FinTech-enabled PPP loan. This result is shown in Table 3. Bivariate regressions, shown in Columns (1) and (2), show an economically and statistically significant effect of bank branches on FinTech lending. A one log-point increase in the number of bank branches decreases the fraction of FinTech loans by about 0.02. Since the median fraction of FinTech loans is about 15%, this means that doubling the number of bank branches in a ZIP code is associated with a decrease in the FinTech share of about 13.3% of the median.

Do ZIP codes with fewer bank branches get more FinTech loans when we control for local demographics? Adding local demographic and income controls slightly increases the estimated relationship between bank branches and the FinTech share of borrowers. Columns (3) and (4) control for median income, the fraction of white population in a ZIP code, and the fraction of population with a commute above 45 minutes. Within a county, areas with lower incomes, longer commutes, and more non-white people have a larger FinTech share of PPP loans. And conditional on these controls, the coefficient on log bank branches rises from 0.02 to 0.025.

As a robustness check, Table A4 in the Appendix shows results from similar specifications at the *loan* level. The results are similar. Loan level specifications allow us to control for differences in borrower characteristics which may affect the riskiness of the loans. All the specifications in this table control for borrower industry. Since we use 6-digit NAICS industries, the NAICS industry likely proxies for many types of borrower differences. We also add controls for average establishment size and local demographics. Throughout, the effect of bank branches on the Fintech share remains negative and statistically significant, and it does not change much even after including

NAICS6 fixed-effects.

The economic effects of the COVID-19 epidemic were unevenly distributed during the time period we study. As we show in Table 2 for two phases separately, borrowers in areas with a worse shock are more likely to take PPP loans. Next, we ask whether the interaction between the COVID shock and bank branch location matter — that is, whether FinTech loans were originated in areas that both had a bad shock and also lacked traditional bank branches. To answer this question, we again measure the COVID shock using both the rise in unemployment at the county level (between the months of March and April) and the number of cases per 100 people.

The results are shown in Table 4, where Columns (1) and (3) use Commuting Zone rather than county fixed effects so that the Case Rate and Unemployment Rate main effects — which are measured at the county level — are identified. We find that the effect of COVID cases on FinTech lending is reduced in areas with more bank branches (see Columns (2)). Interpreting the coefficients in the first two columns, one more case per 1,000 people means that FinTechs originate about 9 percentage points more of the local PPP loans on average. But in areas with one log point more branches, the effect of each COVID case on the FinTech fraction is reduced by about 10%. In other words, adding one log point more branches reduces the effect of one COVID case per 1,000 from about 9 percentage points to about 8 percentage points. Likewise, bank branches intermediate the effect of unemployment on PPP loans. Shown in Columns (3) and (4), areas where the unemployment rate grew by 1 percentage point more had 1.5 percentage points more of their PPP loans coming from FinTechs. But if the number of bank branches rises by one log-point, the effect of a 1 percentage point increase in the unemployment rate on the FinTech share falls to 1.0 percentage points.

5.1 Banking Relationships and FinTech Lending

The statistics so far have provided evidence that in lower-income areas and in areas with fewer banks, more borrowers turned to FinTech loans for their PPP. But, we are also interested in directly answering the question of whether firms with less *ex ante* exposure to the formal banking system were more likely to turn to these types of lenders.

To measure exposure to the formal banking system, we measure pre-COVID banking system access at the industry level. To do this, we use SBA data on the 7(a) program from the years 2018 and 2019. The 7(a) program is the main lending program that the SBA uses to support small businesses. Since it is administered through the same types of institutions as the PPP program, firms in industries which previously used 7(a) loans are likely to have *ex ante* banking relationships. Therefore, we measure which industries disproportionately got PPP loans *relative* to how many SBA loans they previously used. Small businesses in industries which demanded many PPP loans, but previously had few SBA 7(a) loans, are unlikely to have strong relationships with banks. On the other hand, small businesses in industries where SBA 7(a) loans are common are more likely to have a formal banking relationship. Therefore, we measure the log ratio of PPP loans in the sample relative to SBA 7(a) loans from the previous two years. We construct this measure at the 6-digit NAICS industry level.

These estimates are shown in Table 5. As shown in Column (1) of this table, businesses in industries with a higher PPP demand shock *relative* to the SBA 7(a) lending quantity were more likely to go online or turn to nonbanks. Applying the estimates in Column 1, firms in an industry with 10 percent more PPP loans than SBA loans would get 0.2 percentage points more of their PPP loans from FinTechs,

relative to firms in an industry with the same number of PPP as SBA loans. While 0.2 percentage points sounds small, it is economically meaningful given that only 10 percent of all PPP loans are from FinTechs. Column (2) adds controls for fixed effects at the NAICS 2-digit level. We do this to ensure the robustness of the results to differences in industry exposure to COVID at the sector level. When we add these controls, the coefficient on the SBA loan access measure increase and remain highly statistically significant.

Another measure of exposure to traditional banking we use is presented in Columns (3)-(4) of Table 5: whether firms that applied for the PPP loans are structured as a sole proprietorship or as a self-employed individuals. These *one-person* firms, which are unlikely to have a formal borrowing relationship with a traditional bank, are more than 20 percentage points more likely to borrow from a FinTech PPP provider. As expected, this effect is very significant not only statistically but also economically.

In the last two columns of Table 5, we use industry-level employment growth, which is a four-week change in unemployment insurance claims by April 11. We find that firms from industries with larger growth around the COVID-19 shock rely less on FinTech PPP loans. In other words, FinTech PPP loans have reached to harder-hit industries that were underserved by banks.

These results show that banks base their lending on past relationships and constrain themselves around their branches. FinTech lenders do not have geographic constraints based on the presence of loan officers or physical bank branches. Despite this, there are a few reasons to think that relationships, or something akin to relationships, might matter for FinTechs. First, borrowers might not know about the possibility of getting a PPP loan through an online bank unless they have done it before. Therefore, areas with many FinTech borrowers in the past might be disproportinately served by FinTech lenders during the PPP program. Second, small

businesses might use online banks for other types of financial services, such as deposits or credit cards. Such borrowers might also trust the same firms to supply PPP loans for them. In both cases, we would expect areas with a large historical FinTech presence to have more PPP loans as well.

To understand whether "relationships" matter for FinTechs, we measure how many SBA 7(a) loans came from FinTechs in the years before the COVID crisis and ask whether this is associated with borrowers getting PPP loans from FinTechs as well. To do this, we match lender names from the 7(a) program to the classification which we create for the PPP program. Less than 2% of 7(a) loans made from 2014-2018 come from lenders which did not make PPP loans, and which we therefore do not classify. Among 7(a) loans we do classify, about 5% come from online banks and about 1.5% come from nonbank lenders. Many of the most important nonbank FinTech lenders, such as Kabbage, Inc., have no history of originating 7(a) loans at all. There is substantial heterogeneity by ZIP code in terms of the share of loans coming from FinTech lenders.

The estimates in Table 6 Columns (1)-(2) present the relationship between the share of 7(a) loans in each ZIP code coming from FinTech lenders and the share of PPP loans coming from them. We find that geographic persistence matters for FinTech lenders, but it is not the only important factor. On the one hand, the estimated effect of 7(a) lending from FinTechs on the FinTech share of PPP loans is statistically significant at the 5% level when we include control variables. On the other hand, the point estimate is economically very small – not different from zero without controls and 0.017 including controls. Moreover, the coefficient on log bank branches is still significant when we include the FinTech fraction of 7(a) loans as a control variable and the estimate is similar to the estimates in Table 3.

Although we show that FinTech lenders serve underserved populations and areas,

an important potential constraint for borrowers' access to FinTech lenders is the access to information online. Therefore, we explore next whether FinTech lending is larger in areas with larger fraction of population with a computer. Both regressions are run at the Zip code level with country fixed effects included and presented in the last two columns of Table 6. Interestingly, we find a negative and significant coefficient in Column (3); however, in Column (4), this coefficient turns to be positive and significant when we control for the median income and other demographic characteristics of the Zip codes in addition to the number of bank branches. A possible reason for this is that computer access is positively correlated with income, banking system access, etc., so without controlling for these factors, the estimated relationship between computer access and FinTech usage is spuriously negative.

Overall, we find that geography matters more for traditional banks than for FinTech lenders. While FinTech lenders do provide PPP loans in areas that they have lent in the past, this effect is not strong. Rather, they focus on facilitating transactions for any borrower with a computer.

6 Predicting Traditional Banks' PPP Provision

What explains why areas with more bank branches have a lower share of FinTech PPP loans? One possibility is that FinTech lenders and traditional banks serve different types of borrowers, and banks locate their branches close to where their borrowers are located. In other words, regional differences in branch location reflect market segmentation in loan demand. Another possible reason is that traditional banks and FinTech lenders serve the same types of borrowers, but traditional banks constrain their lending to be nearby their branches. If FinTech borrowers' superior technology allows them to lend everywhere, then geographic differences could reflect loan supply

as well.

To shed light on this question, we study whether borrowers substitute to FinTech lenders in regions where traditional banks' loan supply is constrained. If the FinTech and traditional bank markets are highly segmented, then we would not expect much substitution between FinTech and traditional bank PPP loans. On the other hand, if borrowers *perfectly* substitute between banks and non-banks, then in principal it is possible that a reduction in bank lending would not lead to an overall reduction in the provision of PPP loans.

Our identification strategy relies on differences in traditional banks' supply of PPP loans. According to widespread news reports around the time of Phase 1 of PPP, some banks were able to handle the surge in PPP demand much better than others. We exploit these differences and create a measure of predicted bank responsiveness that will allow us to distinguish the possible explanations for our findings. The advantage of measuring predicted responsiveness, rather than realized responsiveness, is that the realized level of responsiveness of local banks may be a function of the magnitude of the COVID shock in each region, which may also have direct effects on the types of PPP loans that borrowers choose. By predicting banks' responsiveness based on their national lending patterns, we hope to create a measure of traditional bank PPP lending that is independent of the number of COVID-19 cases.

We created our predicted-PPP measure in two steps. First, we measure PPP loans per bank branch (PPP loans divided by the number of bank branches) at the bank level nationally in all counties where a bank has branches. This is our measure of bank "responsiveness" to the PPP program. In the second step, we calculate the average responsiveness by ZIP code of banks located there. This yields a prediction for the amount of PPP lending that will take place in each ZIP code. We take the log

of this measure to calculate the log predicted number of PPP loans by ZIP code.[22]

Then, we repeat steps 1-2 separately for each state. We drop each state's own branches and loans and do the calculations in step 1 using loans from *other* states. This ensures that our measure of bank responsiveness in each state is independent of COVID-19 conditions in that state.[23] In this way, we create a measure akin to a shift-share shock (Bartik, 1991), where we quantify the degree of responsiveness, at the bank level, to the PPP program.

As noted, the purpose of measuring PPP responsiveness using bank characteristics is to predict PPP lending independent of the magnitude of the COVID-19 shock. Table A5 in the Appendix verifies that the predicted lending measure is independent of our two proxies for the size of the COVID shock — the increase in the unemployment claims rate from March 15 to April 11, and the average COVID case rate in March. Ideally, we would measure these variables at the ZIP code level and use specifications with county fixed effects. Since these variables are only available at the county level, this table uses Commuting Zone fixed effects instead. We also include specifications which control for the number of bank branches per ZIP.[24]

Next, we verify that in ZIP codes with more responsive banks, more PPP lending is provided overall. These results are shown in Appendix Table A7. For this table, we include county fixed effects and weight estimates by the number of branches in the

[22]Since this variable is only available in ZIP codes with bank branches, estimates using predicted loan amounts will have about half as many observations as the previous tables.

[23]To see why this is important, consider the example of two community banks, each located in only one state, where their states have different PPP demand shocks. The bank located in the high-shock state would appear more "responsive" to the program because it would originate more loans per branch. But, this would be coming from differences in loan demand, not loan supply.

[24]An implicit assumption of this approach is that banks are more likely to make PPP loans in ZIP codes where their branches are located. Table A6 of the Appendix shows that this is true. Column 1 shows the results of bank-by-ZIP code level specifications for each ZIP code where banks have branches. We also show results from a specification with ZIP code fixed effects in Column 2. The large positive coefficient in this column means that, within ZIP code, banks with more branches originate more PPP loans. Finally, Column 3 adds bank fixed effects, so the results are driven by within-bank, cross-ZIP code variation. The coefficient does not vary much across columns.

ZIP code. We also add the total number of bank branches as an additional control variable. The variable of interest is labeled "Predicted PPP" and it measures the log predicted number of PPP loans by ZIP code. Since online banks have few branches but many loans, they would appear highly responsive. To minimize the influence of any online banks we may have missed in our classification, this table also shows versions of the predicted measure at different levels of Winsorization. The coefficients on the Winsorized measures are larger than the un-Winsorized ones, as we expect, given that this measure minimizes the influence of online banks. Therefore, we use the predicted PPP measure that is Winsorized at the bank level at the 95th percentile.

Table 7 shows the effect of predicted PPP bank lending on the log number of FinTech loans per establishment. Column (1) shows the bivariate relationship, Column (2), adds the total number of bank branches as an additional control variable and in Column (3) adds further demographic controls. Estimates are weighted by establishments per ZIP code; but, weighting by PPP loans per ZIP code or using log(PPP/Establishments) as a dependent variable yields similar results. The negative, statistically significant coefficients in this table means that ZIP codes with more responsive traditional banks have a lower number of loans from FinTech lenders. In ZIP codes where local banks are predicted to make more PPP loans, there is less FinTech PPP lending per establishment.

While the results in this table are statistically significant, the degree of substitution between FinTechs and traditional banks is economically small. According to our preferred specification, shown in Column (3), the elasticity of FinTech lending with respect to predicted traditional bank lending is approximately -0.04. This coefficient indicates that a 10 percent decrease in traditional bank lending causes approximately a 0.4 percent increase in FinTech lending. Since FinTech lending is about 15 percent of overall PPP lending, the number of FinTech loans that are made as a result is only

0.3 percent of the decrease in traditional bank lending.

This finding indicates that substitution from traditional banks to FinTechs is not enough to substantially replace traditional bank PPP loans that are not made because banks were not responsive to the program. But the estimate comes from ZIP codes where bank branches are located, and the estimates are weighted by the number of branches per ZIP code. Substitution may be larger in ZIP codes where fewer branches operate, in other words, the ZIP codes where FinTech loans are more common.

7 Conclusion

This papers studies whether FinTech lenders provide access to financial services for regions and borrowers that are not served by the traditional banking system. When we compare different regions of the country, these Fintech online banks and nonbank lenders are concentrated in coastal areas and cities — regions that have better access to banks and better access to financial services.

Within counties, FinTech lenders disproportionately serve industries and ZIP codes with less access to traditional finance. ZIP codes with fewer bank branches and a lower median income get more of their PPP loans from these types of new lenders. Across industries, firms in industry codes who previously got fewer SBA loans were more likely to get their PPP loans from FinTech lenders. Finally, we show that in ZIP codes where lenders did not do much PPP origination, only a small fraction of local small businesses turned to FinTech online banks and nonbanks instead.

We study systematically the first government program, where traditional banks and FinTech lenders have been compared in terms of their responsiveness to the demand for exactly the same type of financial service. Therefore our paper has important policy implications. These implications speak to allowing (more) FinTech

lenders in a timely manner to participate in any type of fully or partially-guaranteed government loan program (e.g., SBA 7a loans) to increase the efficiency of small-business lending not only during crises but also in non-crises periods. Moreover, we have focused on online FinTech lenders which do not engage in traditional banking. But traditional banks may also use technology-enabled credit scoring or loan application mechanisms. Whether they do so in a different way than specialized FinTech lenders is a fruitful area for future research.

References

Abrams, Eliot, "Assessing Bank Deposit Market Power Given Limited Consumer Consideration," 2019. University of Chicago Working Paper.

Autor, David, David Cho, Leland Crane, Mita Goldar, Byron Lutz, Joshua Montes, William Peterman, David Ratner, Daniel Villar, and Ahu Yildirmaz, "An Evaluation of the Paycheck Protection Program Using Administrative Payroll Microdata," 2020. MIT Working Paper.

Balyuk, Tetyana, Allen Berger, and John Hackney, "What is Fueling FinTech Lending? The Role of Banking Market Structure," 2020. Emory University Working Paper.

Banerjee, Abhijit and Esther Duflo, "Do Firms Want to Borrow More? Testing Credit Constraints Using a Directed Lending Program," *Review of Economic Studies*, 2014, *81*, 572–607.

Barrios, John, Michael Minnis, William Minnis, and Joost Sijthoff, "Assessing the Payroll Protection Program: A Framework and Preliminary Results," 2020. University of Chicago Working paper.

Bartik, Alexander W, Marianne Bertrand, Zoë B Cullen, Edward L Glaeser, Michael Luca, and Christopher T Stanton, "How are small businesses adjusting to covid-19? early evidence from a survey," Technical Report, National Bureau of Economic Research 2020.

Bartik, Timothy J, "Who benefits from state and local economic development policies?," 1991.

Berlin, Mitchell, Greg Nini, and Edison Yu, "Concentration of Control Rights in Leveraged Loan Syndicates," 2018. Federal Reserve Bank of Philadelphia Working Paper.

Biswas, Swarnava, Neslihan Ozkan, and Junyang Yin, "Real Effects of Nonbank Lending," 2018. University of Bristol Working Paper.

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru, "Fintech, regulatory arbitrage, and the rise of shadow banks," *Journal of Financial Economics*, 2018, *130*, 453–483.

Butler, Alexander, Jess Cornaggia, and Umit Gurun, "Do Local Capital Market Conditions Affect Consumers' Borrowing Decisions?," *Management Science*, 2016, *63*, 3999–4446.

Carlin, Bruce, Arna Olafsson, and Michaela Pagel, "FinTech and Consumer Well-Being in the Information Age," 2020. UCLA Working Paper.

Chernenko, Sergey, Isil Erel, and Robert Prilmeier, "Why Do Firms Borrow Directly from Nonbanks?," 2019. NBER Working Paper.

Chetty, Raj, John N Friedman, Nathaniel Hendren, and Michael Stepner, "How did covid-19 and stabilization policies affect spending and employment? a new real-time economic tracker based on private sector data," Technical Report, National Bureau of Economic Research 2020.

Claire, Lelarge, David Sraer, and David Thesmar, *Entrepreneurship and Credit Constraints Evidence from a French Loan Guarantee Program* 2010. NBER Working Paper.

Cole, Rebel, Douglas Cumming, and Jon Taylor, "Does FinTech Compete with or Complement Bank Finance?," 2019. Working paper.

Cororaton, Anna and Samuel Rosen, "Public Firm Borrowers of the US Paycheck Protection Program," 2020. SMU Working Paper.

Cortes, Kristle, Yuliya Demyanyk, Lei Li, Elena Loutskina, and Philip Strahan, "Stress Tests and Small Business Lending," *Journal of Financial Economics*, 2020, *136*, 260–279.

Davydiuk, Tetiana, Tatyana Marchuk, and Samuel Rosen, "Direct Lending in the U.S. Middle Market," 2020. Carnegie Mellon University Working Paper.

de Roure, Calebe, Loriana Pelizzon, and Anjan Thakor, "P2P lenders versus banks: Cream skimming or bottom fishing?," 2018. Washington University Working Paper.

Fahlenbrach, Rüdiger, Kevin Rageth, and René M Stulz, "How valuable is financial flexibility when revenue stops? Evidence from the Covid-19 crisis," Technical Report, National Bureau of Economic Research 2020.

Falato, Antonio, Itay Goldstein, and Ali Hortaçsu, "Financial Fragility in the COVID-19 Crisis: The Case of Investment Funds in Corporate Bond Markets," Technical Report, National Bureau of Economic Research 2020.

Fuster, A., M. Plosser, P. Schnabl, and J. Vickery, "The role of technology in mortgage lending," *Review of Financial Studies*, 2019, *32*, 1854–1899.

Gopal, Manasa and Philipp Schnabl, "The Rise of Finance Companies and FinTech Lenders in Small Business Lending," 2020. New York University Working Paper.

Granja, Joao, Christos Makridis, Constantine Yannelis, and Eric Zwick, "Did the Paycheck Protection Program Hit the Target?," 2020. University of Chicago Working Paper.

Green, Daniel and Erik Loualiche, "Local Government Finances and Balanced Budgets in the COVID-19 Crisis," *Available at SSRN 3651605*, 2020.

Halling, Michael, Jin Yu, and Josef Zechner, "How Did COVID-19 Affect Firms' Access to Public Capital Markets?," *The Review of Corporate Finance Studies*, 2020.

Hamilton, Steven and Stan Veuger, "How to Help American Businesses Endure and Jobs Survive," Technical Report, George Washington University Working Paper 2020.

Hanson, Samuel G., Andrei Shleifer, Jeremy C. Stein, and Robert W. Vishny, "Banks as patient fixed-income investors," *Journal of Financial Economics*, 2015, *117*, 449–469.

Irani, Rustom, Rajkamal Iyer, Ralf Meisenzahl, and Jose-Luis Peydro, "The Rise of Shadow Banking: Evidence from Capital Regulation," 2020. Working Paper.

Ivashina, Victoria and Zheng Sun, "Institutional demand pressure and the cost of corporate loans," *Journal of Financial Economics*, 2011, *99*, 500–522.

Jiang, Wei, Kai Li, and Pei Shao, "When shareholders are creditors: Effects of the simultaneous holding of equity and debt by non-commercial banking institutions," *Review of Financial Studies*, 2010, *23*, 3595–3637.

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

Liebersohn, Jack, "Are Retail Banking Markets Still Local? Quasi-Experimental Evidence from Bank Mergers," 2020. Ohio State University Working Paper.

Lim, Jongha, Bernadette A. Minton, and Michael S. Weisbach, "Syndicated loan spreads and the composition of the syndicate," *Journal of Financial Economics*, 2014, pp. 45–69.

Maggio, Marco Di and Vincent Yao, "FinTech borrowers: Lax-Screening or cream-skimming?," 2018. HBS Working Paper.

Manson, Steven, Jonathan Schroeder, David Van Riper, and Steven Ruggles, "IPUMS National Historical Geographic Information System: Version 12.0 [Database]," *Minneapolis: University of Minnesota*, 2017, *39*.

Massoud, Nadia, Debarshi Nandy, Anthony Saunders, and Keke Song, "Do hedge funds trade on private information? Evidence from syndicated lending and short-selling," *, Journal of Financial Economics*, 2011, *99*, 477–499.

Mills, Karen, *Fintech, Small Business the American Dream: How Technology Is Transforming Lending and Shaping a New Era of Small Business Opportunity* 2018. Published by Palgrave Macmillan.

_ **and Annie Dang**, "Building Small Business Utopia: How Artificial Intelligence and Big Data Can Increase Small Business Success In Big Data in Small Business," 2020. Harvard Business School Working Paper.

Morse, Adair, "Peer-to-Peer Crowdfunding: Information and the Potential for Disruption in Consumer Lending," *Annual Review of Financial Economics*, 2015, *7*, 463–482.

Nadauld, Taylor D. and Michael S. Weisbach, "Did securitization affect the cost of corporate debt?," *Journal of Financial Economics*, 2012, *105*, 332–352.

Pastor, Lubos and M Blair Vorsatz, "Mutual fund performance and flows during the COVID-19 crisis," Technical Report, National Bureau of Economic Research 2020.

Philippon, Thomas, "Has the US Finance Industry Become Less Efficient? On the Theory and Measurement of Financial Intermediation," *American Economic Review*, 2015, *105*, 1408–1438.

Stulz, Rene, "FinTech, BigTech, and the Future of Banks," *Journal of Applied Corporate Finance*, 2019, *31*, 86–97.

Tang, H., "Peer-to-Peer Lenders versus Banks: Substitutes or Complements?," *The Review of Financial Studies*, 2019, *32*, 1900–1938.

Vallee, B. and Y. Zeng, "Marketplace lending: A new banking paradigm?," *Review of Financial Studies*, 2019, *32*, 1939–1982.

Yanofsky, David, "Here's what we know is wrong with the PPP data," 2020.

Figures

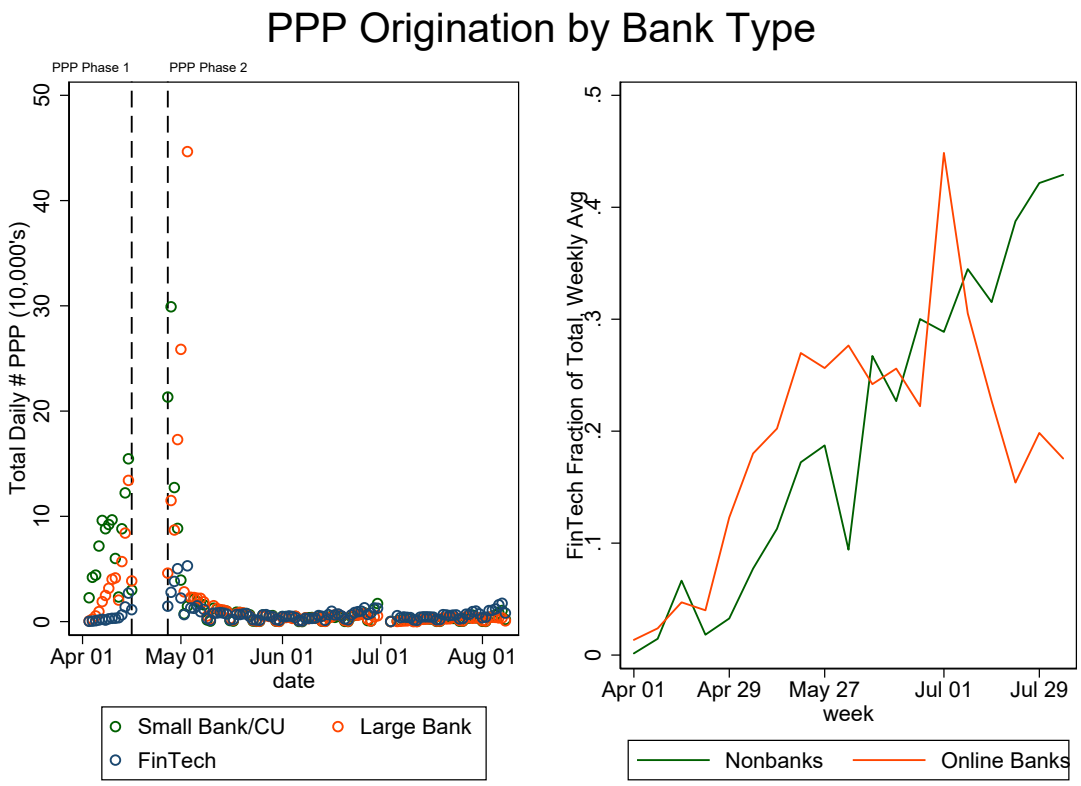
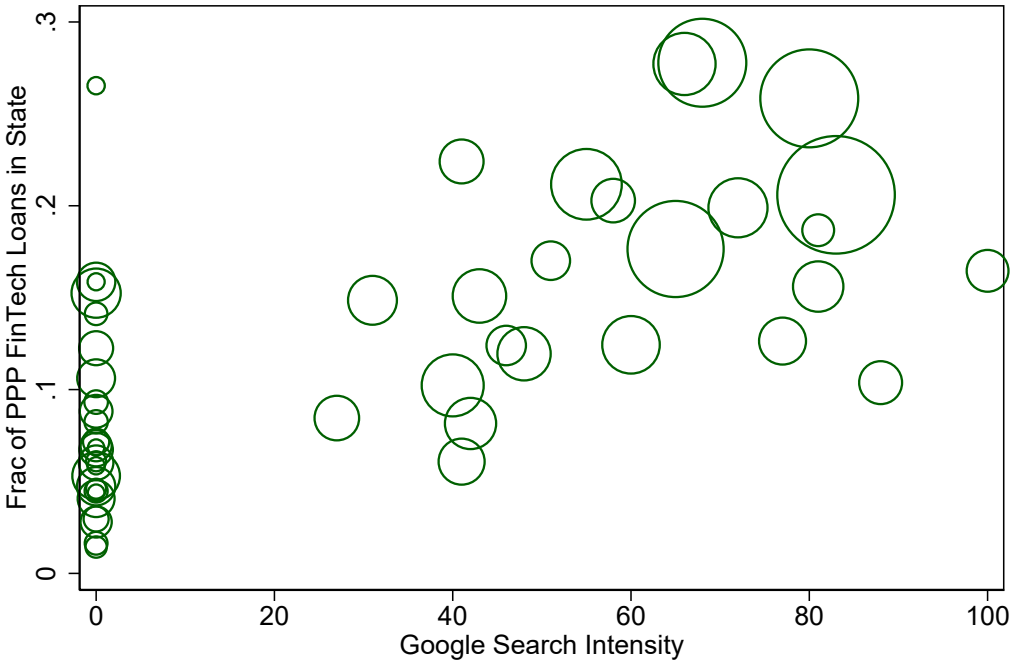


Figure 1: PPP Lending by Day and Type of Institution. Panels show the number of PPP loans given by various lenders daily between April 3 and August 8, 2020. "Large banks" are banks with more than $20 billion in assets, "Small Bank/CU" includes all other lenders except FinTech, including unclassified lenders. Source: Calculated from SBA PPP Loan Databse.



Source: Google Trends. Searches for "apply ppp loan online" from 3/1/20 to 8/8/20.
Each circle represents a state. Weighted by the total number of PPP loans in each state.

Figure 2: Google Searches for Online PPP Loans.

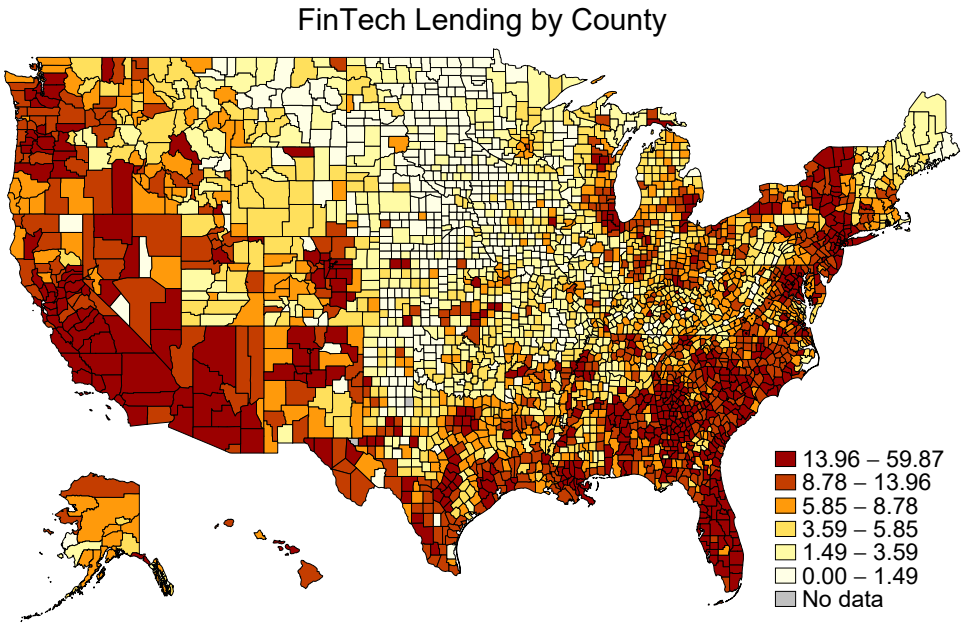


Figure 3: Fraction of PPP Loans from FinTech Lenders, U.S. Counties

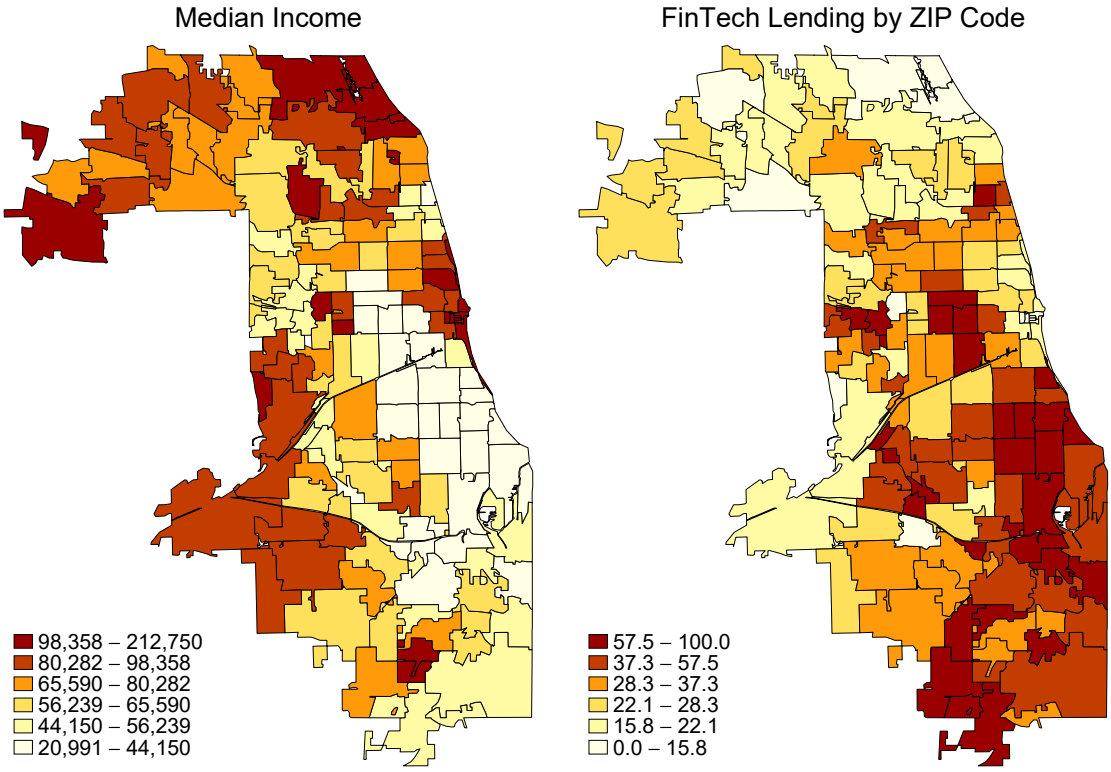


Figure 4: Fraction of PPP Loans from FinTech Lenders, Chicago ZIP Codes.

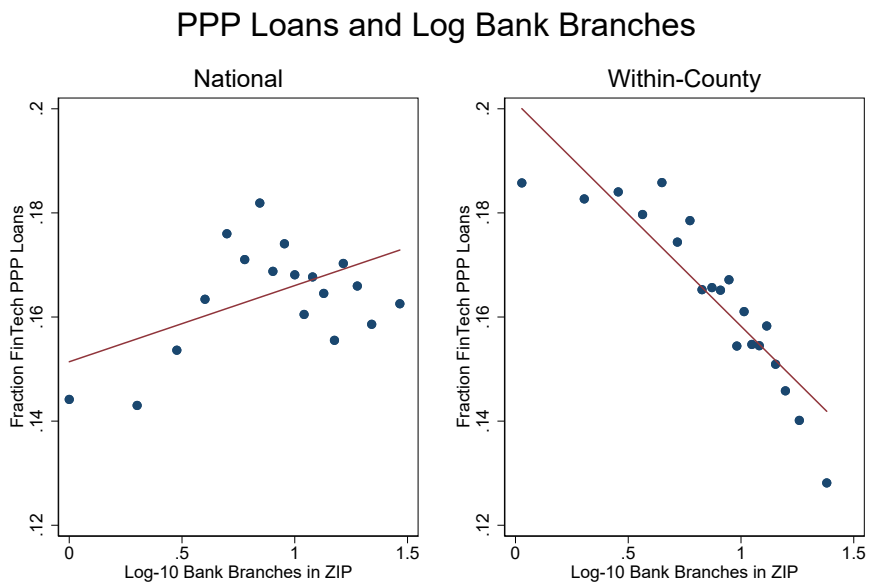


Figure 5: Lending Share and Log Bank Branches.

Tables

Table 1: Summary Statistics by ZIP Code

	Mean	Std. Dev	Median	Count
Frac Nonbank	0.07	0.06	0.05	36,675
Frac Online Bk	0.10	0.07	0.09	36,675
Total FinTech PPP Fraction	0.16	0.12	0.15	36,675
Frac Bk/CU	0.83	0.12	0.84	36,675
Num. PPP Lns	628.56	534.53	515.00	36,675
Median Income	70,469.32	29,818.04	63,945.00	30,002
Frac. 45m+ Commute	0.17	0.10	0.14	31,190
Frac. White	0.74	0.21	0.80	31,501
Total Pop	13,735.63	9,091.73	12,730.00	31,565
Num. Bk Branches	9.44	7.21	8.00	19,404
Avg COVID Case Rate	0.02	0.04	0.00	35,749
Unemp. Growth	3.35	1.83	3.01	17,176
Num. Estabs	924.14	782.22	771.00	33,955

Weighted by PPP loans per zip code. Bank branches are for ZIP codes that have at least one branch. Unemployment data is not available for all regions. Source: Calculated from SBA PPP database, FDIC SOD, Decennial Census/ACS, County Business Patterns.

Table 2: Geographic Correlates of PPP Provision

	(1)	(2)	(3)	(4)	(5)	(6)
	Log PPP Trad. Bk Phase 1	Log PPP FinTech Phase 1	Log PPP Trad. Bk Apr 12-16	Log PPP FinTech Apr 12-16	Log PPP Trad. Bk Phase 2	Log PPP FinTech Phase 2
Avg Case Rate	-4.17***	-0.035	-2.50***	0.12	0.28***	4.94***
	(0.23)	(0.25)	(0.21)	(0.25)	(0.077)	(0.19)
Change in Unemployment	-0.071***	0.072***	-0.052***	0.067***	0.033***	0.14***
	(0.0056)	(0.0078)	(0.0044)	(0.0077)	(0.0025)	(0.0088)
Log Establishments	0.89***	1.07***	0.91***	1.01***	0.97***	1.07***
	(0.0066)	(0.015)	(0.0058)	(0.016)	(0.0033)	(0.0086)
Constant	-0.85***	-5.27***	-1.73***	-5.07***	-0.97***	-3.47***
	(0.040)	(0.094)	(0.035)	(0.10)	(0.020)	(0.055)
Observations	14724	6432	13454	5974	15639	10866
R^2	0.748	0.562	0.804	0.527	0.913	0.714

ZIP code level specifications showing the relationship between COVID-19 shock and the degree of PPP origination, for traditional banks and for FinTech lenders. Robust standard errors. Estimates are weighted by PPP loans per ZIP code. Data calculated from Chetty et al. (2020) and SBA PPP loan data.

Table 3: Number of Branches in the ZIP Code and FinTech PPP Lending Shares

	(1) FinTech PPP Fraction	(2) Bank PPP Fraction	(3) FinTech PPP Fraction	(4) Bank PPP Fraction
Log Branches	-0.019***	0.020***	-0.025***	0.026***
	(0.0010)	(0.0010)	(0.0013)	(0.0013)
Log Med. Inc			-0.012***	0.014***
			(0.0035)	(0.0035)
Frac Commute 45+m			0.19***	-0.20***
			(0.014)	(0.014)
Frac White			-0.18***	0.18***
			(0.0089)	(0.0088)
Log Population			0.025***	-0.025***
			(0.0011)	(0.0012)
Establishments Per Cap.			-0.0049	0.0059
			(0.0051)	(0.0054)
Constant	0.20***	0.79***	0.22***	0.75***
	(0.0022)	(0.0022)	(0.035)	(0.035)
Observations	35937	35937	28850	28850
R^2	0.706	0.684	0.808	0.790
County FEs	X	X	X	X

ZIP code level specifications showing the relationship between the share of FinTech PPP lending and the number of bank branches per ZIP code. Robust standard errors. Estimates are weighted by PPP loans per ZIP code. Data calculated from Chetty et al. (2020) and SBA PPP loan data.

Table 4: Increases in County Unemployment and PPP Origination

	(1) FinTech PPP Fraction	(2) FinTech PPP Fraction	(3) FinTech PPP Fraction	(4) FinTech PPP Fraction
Case Rate	0.89***			
	(0.24)			
Log Branches	-0.017***	-0.017***	-0.018***	-0.00074
	(0.0028)	(0.0031)	(0.0039)	(0.0080)
Case Rate × Log Branches		-0.097**		
		(0.047)		
Unemp. Chg			0.016***	
			(0.0047)	
Unemp. Chg × Log Branches				-0.0054***
				(0.0018)
Constant	0.18***	0.20***	0.16***	0.22***
	(0.0068)	(0.0060)	(0.016)	(0.0085)
Observations	35727	35749	17173	17176
R^2	0.604	0.702	0.588	0.713
County FEs		X		X
CZ FEs	X		X	

Specifications showing the relationship between the share of FinTech PPP lending and ZIP code level statistics interacted with the change in unemployment and change in case rate. Columns (1) and (3) use Commuting Zone fixed effects because the case rate and change in unemployment are observed at the county level. Standard errors clustered by county. Estimates are weighted by PPP loans per ZIP code. Data calculated from the FDIC Summary of Deposits database and SBA PPP loan data.

Table 5: FinTech Lending and Firm Relationships

	(1)	(2)	(3)	(4)	(5)	(6)
	FinTech PPP Loan	FinTech PPP Loan	FinTech PPP Loan	FinTech PPP Loan	FinTech PPP Loan	FinTech PPP Loan
Log(PPP/SBA 7a)	0.023**	0.029***				
	(0.0097)	(0.011)				
One-Pers. Firm			0.22***	0.21***		
			(0.016)	(0.013)		
Industry Emp. Growth					-0.22**	-0.33***
					(0.085)	(0.081)
Constant	0.076**	0.050	0.12***	0.12***	0.35***	0.44***
	(0.037)	(0.044)	(0.0055)	(0.0052)	(0.076)	(0.068)
Observations	4863168	4863168	5076115	5076115	4035347	4035347
R^2	0.113	0.133	0.161	0.173	0.121	0.142
Zip FEs	X	X	X	X	X	X
NAICS2 FEs		X		X		

Loan-level specifications showing the relationship between FinTech loans and proxies for borrowers' ability to rely on loan relationships. Dependent variable is an indicator equal to 1 if a loan is originated by a FinTech firm. Log(PPP/SBA 7a) measures the number of PPP loans scaled by the number of SBA 7(a) loans in the years 2016-2018, measured at the NAICS 6-digit level. One-Pers. firm is an indicator for sole proprieterships and individuals as indicated in the PPP data. Industry emp. growth measures employment growth by 3-digit NAICS industry between the March and April Current Employment Statistics. Standard errors double-clustered by NAICS 6-digit industry and ZIP code.

Table 6: Local Technology Use and PPP Lending

	(1) FinTech PPP Fraction	(2) FinTech PPP Fraction	(3) FinTech PPP Fraction	(4) FinTech PPP Fraction
7(a) Share	-0.0016	0.015**		
	(0.0093)	(0.0069)		
Fraction w Desktop			-0.25***	0.071***
			(0.014)	(0.020)
Log Med. Inc		-0.012***		-0.026***
		(0.0037)		(0.0044)
Frac Commute 45+m		0.20***		0.19***
		(0.016)		(0.014)
Frac White		-0.18***		-0.18***
		(0.0093)		(0.0094)
Log Branches		-0.025***		-0.025***
		(0.0013)		(0.0013)
Log Population		0.027***		0.024***
		(0.0013)		(0.0012)
Establishments Per Cap.		-0.0030		-0.0059
		(0.0050)		(0.0054)
Constant	0.17***	0.20***	0.36***	0.33***
	(0.0011)	(0.037)	(0.011)	(0.040)
Observations	20467	19219	31316	28846
R^2	0.694	0.812	0.720	0.809
County FEs	X	X	X	X

Estimates show the relationship between ZIP-level measures of technology use and the FinTech fraction of PPP loans. "7(a) Share" measures the fraction of 7(a) loans in the ZIP code coming from FinTech lenders as identified in the PPP data. "Fraction w Desktop" is the fraction of households in the ZIP code with a desktop computer, as reported in the 2014-2018 ACS. Data calculated from SBA 7(a) and PPP data, and US Census/ACS data. Robust standard errors.

Table 7: Effect of Predicted Bank PPP on Total PPP Per Establishment

	(1) FinTech PPP/ Establishments	(2) FinTech PPP/ Establishments	(3) FinTech PPP/ Establishments
Log Pred. PPP	-0.10***	-0.043**	-0.039**
	(0.021)	(0.020)	(0.018)
Bk Branches		-0.16***	-0.24***
		(0.0086)	(0.0093)
Log Med. Inc.			0.18***
			(0.021)
Frac Commute 45+m			1.00***
			(0.086)
Frac White			-0.79***
			(0.049)
Log Pop			0.20***
			(0.0088)
Constant	-2.26***	-2.12***	-5.35***
	(0.077)	(0.075)	(0.22)
Observations	12695	12695	12547
R^2	0.812	0.822	0.863
County FEs	X	X	X

ZIP code level specifications showing the relationship between the share of PPP lending per establishment and the predicted level of PPP lending based on banks' overall degree of PPP lending. Robust standard errors. Estimates are weighted by establishments per ZIP code. Weighting by PPP loans per ZIP code or using log(PPP/Establishments) as a dependent variable yields similar results. Data calculated from ZIP business patterns and SBA PPP loan data.

A Appendix

Table A1: Summary Statistics by ZIP Code (unweighted)

	Mean	Std. Dev	Median	Count
Frac Nonbank	0.05	0.10	0.01	36,675
Frac Online Bk	0.06	0.10	0.02	36,675
Total FinTech PPP Fraction	0.10	0.15	0.06	36,675
Frac Bk/CU	0.88	0.16	0.92	36,675
Num. PPP Lns	142.12	262.93	26.00	36,675
Median Income	59,457.12	25,252.21	54,286.00	30,002
Frac. 45m+ Commute	0.17	0.12	0.15	31,190
Frac. White	0.83	0.20	0.92	31,501
Total Pop	4,558.81	6,742.19	1,306.00	31,565
Num. Bk Branches	4.53	4.90	3.00	19,404
Avg COVID Case Rate	0.01	0.02	0.00	35,749
Unemp. Growth	2.95	1.79	2.63	17,176
Num. Estabs	230.15	403.82	45.00	33,955

Bank branches are for ZIP codes that have at least one branch. Unemployment data is not available for all regions. Source: Calculated from SBA PPP database, FDIC SOD, Decennial Census/ACS, County Business Patterns.

Table A2: Number of Branches in the ZIP Code and PPP Lending Shares, Alternative Measure of FinTech

	(1) FinTech PPP Fraction	(2) FinTech PPP Fraction	(3) FinTech PPP Fraction	(4) FinTech PPP Fraction
Log Branches	-0.020***	0.020***	-0.027***	0.027***
	(0.0010)	(0.0010)	(0.0013)	(0.0013)
Log Med. Inc			-0.014***	0.014***
			(0.0035)	(0.0035)
Frac Commute 45+m			0.20***	-0.20***
			(0.014)	(0.014)
Frac White			-0.18***	0.18***
			(0.0089)	(0.0089)
Log Population			0.026***	-0.026***
			(0.0012)	(0.0012)
Establishments Per Cap.			-0.0056	0.0056
			(0.0053)	(0.0053)
Constant	0.20***	0.80***	0.23***	0.77***
	(0.0022)	(0.0022)	(0.035)	(0.035)
Observations	35884	35884	28834	28834
R^2	0.684	0.684	0.798	0.798
County FEs	X	X	X	X

ZIP code level specifications showing the relationship between the share of FinTech PPP lending and ZIP code level statistics, including the log number of bank branches. This table uses a narrow measure of FinTech lenders as discussed in the text. Robust standard errors. Estimates are weighted by PPP loans per ZIP code. Data calculated from Chetty et al. (2020) and SBA PPP loan data.

Table A3: Number of Branches in the ZIP Code and PPP Lending Shares, Online and Nonbank Lenders

	(1) Online Bk PPP Fraction	(2) Nonbank PPP Fraction	(3) Online Bk PPP Fraction	(4) Nonbank PPP Fraction
Log Branches	-0.0063***	-0.012***	-0.010***	-0.015***
	(0.00054)	(0.00057)	(0.00068)	(0.00070)
Log Med. Inc			-0.0065***	-0.0058***
			(0.0020)	(0.0018)
Frac Commute 45+m			0.086***	0.10***
			(0.0083)	(0.0075)
Frac White			-0.070***	-0.11***
			(0.0051)	(0.0046)
Log Population			0.013***	0.012***
			(0.00063)	(0.00064)
Establishments Per Cap.			-0.0038	-0.0011
			(0.0026)	(0.0029)
Constant	0.11***	0.093***	0.11***	0.11***
	(0.0011)	(0.0012)	(0.020)	(0.019)
Observations	35937	35937	28850	28850
R^2	0.740	0.618	0.805	0.743
County FEs	X	X	X	X

ZIP code level specifications showing the relationship between the share of online and nonbank PPP lending and ZIP code level statistics, including the log number of bank branches. Robust standard errors. Estimates are weighted by PPP loans per ZIP code. Data calculated from Chetty et al. (2020) and SBA PPP loan data.

Table A4: Bank Branch Density and Fraction of Online/Nonbank Loans, Loan Level Estimates

	(1) FinTech PPP Loan	(2) FinTech PPP Loan
Log Bk Branches	-0.022***	-0.019***
	(0.0012)	(0.00096)
Frac White	-0.21***	-0.18***
	(0.0068)	(0.0056)
Frac Commute 45+m	0.14***	0.12***
	(0.013)	(0.011)
Log Pop	0.025***	0.019***
	(0.00092)	(0.00077)
Log Est Size	-0.022***	-0.014***
	(0.0016)	(0.0013)
Constant	0.16***	0.18***
	(0.010)	(0.0086)
Observations	5116435	4988784
R^2	0.080	0.172
County FEs	X	X
NAICS FEs		X

Loan level specifications showing the relationship between the likelihood that a PPP loan is from an online bank/nonbank, and ZIP code level statistics, including the log number of bank branches. Standard errors clustered by ZIP Code. Data calculated from the SBA PPP Loan Database, ZIP Business Patterns, the 2014/2018 ACS and the 2010 Decennial Census.

Table A5: Predicted Bank Lending and the Economic Shock

	(1) Average Case Rate	(2) Average Case Rate	(3) Unemployment Growth	(4) Unemployment Growth
Log Pred. PPP	-0.000082	-0.00055	-0.030	-0.026
	(0.00043)	(0.00044)	(0.050)	(0.050)
Bk Branches		0.0012***		-0.011
		(0.00024)		(0.022)
Constant	0.013***	0.012***	3.24***	3.25***
	(0.0016)	(0.0016)	(0.18)	(0.18)
Observations	13690	13690	6819	6819
R^2	0.852	0.853	0.792	0.792
Commuting Zone FEs		X		X

ZIP code-by-bank level specifications showing the relationship between the predicted number of bank PPP loans, and the magnitude of the COVID-19 economic shock. Robust standard errors. Estimates are weighted by PPP loans per ZIP code. Data calculated from the FDIC Summary of Deposits database, SBA PPP loan data, and data from Chetty et al. (2020).

Table A6: PPP Lending and Bank's Own Branch Locations

	(1)	(2)	(3)
	Log PPP Loans	Log PPP Loans	Log PPP Loans
Bk Branches	2.12***	1.87***	1.99***
	(0.070)	(0.099)	(0.046)
Constant	1.36***	1.64***	1.47***
	(0.086)	(0.093)	(0.036)
Observations	58556	52360	57885
R^2	0.147	0.399	0.438
Bank FEs			X
Zip FEs		X	

ZIP code-by-bank level specifications showing the relationship between the number of PPP loans from a given bank, and the number of branches that that bank has in the ZIP code. Robust standard errors. Estimates are weighted by PPP loans per ZIP code. Data calculated from the FDIC Summary of Deposits database and SBA PPP loan data.

Table A7: Effect of Predicted Bank Lending on Overall Lending

	(1) Log PPP Loans	(2) Log PPP Loans	(3) Log PPP Loans	(4) Log PPP Loans	(5) Log PPP Loans	(6) Log PPP Loans
Bk Branches	0.83***	0.72***	0.83***	0.72***	0.83***	0.72***
	(0.012)	(0.0099)	(0.012)	(0.0099)	(0.012)	(0.0099)
Log Predicted PPP (Winsor 90)	0.51***	0.15***				
	(0.026)	(0.028)				
Log Predicted PPP (Winsor 95)			0.42***	0.12***		
			(0.023)	(0.025)		
Log Predicted PPP (Winsor 100)					0.32***	0.093***
					(0.021)	(0.021)
Constant	2.55***	4.15***	2.87***	4.25***	3.24***	4.34***
	(0.095)	(0.10)	(0.088)	(0.092)	(0.078)	(0.077)
Observations	13841	13814	13841	13814	13841	13814
R^2	0.510	0.789	0.507	0.789	0.502	0.789
County FEs		X		X		X

ZIP code-by-bank level specifications showing the relationship between the predicted number of bank PPP loans, and the total overall number of PPP loans. The PPP measures are Winsorized at the bank level before weighted averages are calculated at the ZIP code level, as discussed in the text. Robust standard errors. Estimates are weighted by PPP loans per ZIP code. Data calculated from the FDIC Summary of Deposits database and SBA PPP loan data.

B Lender Classifications

B.1 Non-Bank FinTech Lenders

Lender	PPP Loans
Kabbage, Inc.	196402
Readycap Lending, LLC	34261
MBE Capital Partners	23945
Intuit Financing Inc.	19086
Fundbox, Inc.	14281
Newtek Small Business Finance, Inc.	11677
New York Business Development Corporation	6468
FC Marketplace, LLC (dba Funding Circle)	6235
Harvest Small Business Finance, LLC	5353
CDC Small Business Finance Corporation	4095
BSD Capital, LLC dba Lendistry	4076
Itria Ventures LLC	3556
Fountainhead SBF LLC	3453
Hope Enterprise Corporation	2869
Accion	2483
CRF Small Business Loan Company, LLC	2398
Fund-Ex Solutions Group, LLC	1416
Montana Community Development Corp.	1276
Mortgage Capital Development Corporation	1122
LiftFund, Inc.	1036
Opportunity Fund Community Development	990
Prestamos CDFI, LLC	938
Centerstone SBA Lending, Inc.	898
Trenton Business Assistance Corporation	894
Benworth Capital	779
Colorado Enterprise Fund	779
Arkansas Capital Corporation	771
Grow America Fund, Incorporated	715
Colorado Lending Source, Ltd.	612
Accion East, Inc.	560
American Lending Center	555
Hana Small Business Lending, Inc.	504

B.2 Online Bank FinTech Lenders

Lender	PPP Loans
Cross River Bank	198738
Celtic Bank Corporation	147317
WebBank	76578
Capital One, National Association	15772
Live Oak Banking Company	11045
American Express National Bank	6964
Signature Bank	6311
Radius Bank	6224
First Bank of the Lake	4199
Transportation Alliance Bank, Inc. d/b/a TAB Bank, Inc.	1687
Pacific Enterprise Bank	1388
The Bancorp Bank	1288
Savoy Bank	1165
American Business Bank	1072
First Secure Bank and Trust Co.	1033
Union National Bank	956
Ally Bank	943
T Bank, National Association	922
Primary Bank	918
Endeavor Bank	860
The MINT National Bank	859
Axos Bank	853
LCA Bank Corporation	825
Signature Bank, National Associatioin	777
Vinings Bank	740

Lender	PPP Loans
FinWise Bank	699
St. Louis Bank	674
Solera National Bank	665
Fresno First Bank	656
Optus Bank	641
Continental Bank	635
Loyal Trust Bank	626
First Command Bank	621
Lexicon Bank	616
Keystone Bank, National Association	612
Chain Bridge Bank, National Association	588
The Victory Bank	579
Bankers' Bank of Kansas	559
Bank of San Francisco	542
Buckeye State Bank	531
Beacon Community Bank	522
Small Business Bank	520
New Valley Bank and Trust	519
TIAA Bank, A Division of	273

B.3 Online Bank FinTech Lenders, Alternative Definition

Lender	PPP Loans
Cross River Bank	198738
Celtic Bank Corporation	147317
WebBank	76578
Capital One, National Association	15772
American Express National Bank	6964
Radius Bank	6224
The Bancorp Bank	1288
Ally Bank	943
Axos Bank	853
OneWest Bank, A Division of	840
FinWise Bank	699
First Internet Bank of Indiana	447
TIAA Bank, A Division of	273
Green Dot Bank	17

C Variable Definitions

Variable	Source	Description
Frac Nonbank	SBA PPP Database	Frac from lenders with above 750 loans with no match in the FFIEC Attributes File or otherwise using news reports.
Frac Online Bk	SBA PPP Database	Frac from lenders with one branch and at least 500 PPP loans or identified using news reports.
Total FinTech PPP Fraction	SBA PPP Database	Fraction from either nonbank or online bank PPP lenders.
One-Pers. Firm	SBA PPP Database	Indicator equal to 1 for borrowers with business type "Sole Proprietorship" or "Self-Employed Individuals"
Frac Traditional Bk/CU	SBA PPP Database	Fraction of loans from non-FinTech lenders that match to FFIEC Attributes file.
Median Income	American Community Survey, 2014-2018	Median Income
Frac 45m+ Commute	American Community Survey, 2014-2018	Fraction of HHs with commute time greater than or equal to 45 minutes
Frac. White	American Community Survey, 2014-2018	Fraction of individuals reporting "White" as only race
Total Pop	American Community Survey, 2014-2018	Total population
Fraction w Desktop	American Community Survey, 2014-2018	Fraction of HHs with desktop computer
Num. Bk. Branches	FDIC Summary of Deposits Database	Number of bank branches in ZIP code
Avg COVID Case Rate	The New York Times, as collected by Chetty et al. (2020)	Avg number of active COVID cases per 100 people in March, by county
Unempl. Growth	State Agencies, as collected by Chetty et al. (2020)	Four-week change in unemployment insurance claims as of April 11, 2020, by County
Num. Estabs	ZIP Business Patterns	Number of establishments in ZIP Code, 2017
PPP/SBA 7(a)	SBA PPP and 7(a) databases	Ratio of PPP loans to SBA 7(a) loans from 2014-2018, by NAICS 5-digit industry

Continued on next page

Table A8 – continued from previous page

Variable	Source	Description
Fraction of 7(a) loans from FinTech	SBA 7(a) data	Fraction of 7(a) loans where lender name matches a PPP FinTech lender