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Can FinTech reduce disparities in access to finance? Evidence from the Paycheck Protection Program

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ABSTRACT

New technology promises to expand the supply of financial services to small businesses poorly served by banks. Does it succeed? We study the response of FinTech to financial services demand created by the introduction of the Paycheck Protection Program. FinTech is disproportionately used in ZIP codes with fewer bank branches, lower incomes, and more minority households, and in industries with fewer banking relationships. It is also greater in counties where the economic effects of the COVID-19 pandemic were more severe. Substitution between FinTech and banks is economically small, implying that FinTech mostly expands, rather than redistributes, the supply of financial services.

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1. Introduction

The COVID-19 pandemic created “a crisis like no other,” with a global economic contraction of 3.1 percent in 2020.[1] To support small businesses through the crisis, the U.S. government created the Paycheck Protection Program (PPP), which offered guaranteed and potentially-forgivable small businesses loans.[2] With $669 billion to be disbursed over a period of a few months in 2020, the PPP was unprecedented in speed and scale.[3] To meet the extraordinary demand for the loans, the Small Business Administration (SBA) made the last-minute, first-time-ever decision to approve a number of non-traditional lenders specializing in Financial Technology (FinTech) to distribute PPP funds directly alongside traditional banks.[4] What effect did allowing FinTechs to participate have on the provision

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[1] World Economic Outlook Update, International Monetary Fund, October 2021.

[2] 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 as of March 2022.

[3] For comparison, the 7(a) program, which is SBA's main lending program, has guaranteed between $10 billion and $20 billion per year since 2010.

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of financial services and on financial inclusion for small businesses? Our paper answers this important question.

This multi-billion-dollar "experiment" to approve FinTech lenders with the exogenous demand shock created by the COVID-19 crisis and the PPP program provide a unique opportunity to study how FinTech changes the supply of financial services. Non-traditional and FinTech lenders are a relatively new but rapidly growing phenomenon. How they impact the commercial credit market will have important consequences for small businesses' credit access, especially in ZIP codes with limited access to the banking system.

We find that FinTech is disproportionately used in areas with fewer bank branches, lower incomes, and a larger share of the minority population. When we focus on areas with bank branches and study substitution between FinTech lenders and traditional banks, we find that the substitution is economically small, indicating that FinTech lenders are reaching new types of customers – i.e., small businesses in areas underserved by the banks.

Why was the decision to approve FinTech lenders unusual? Although the role of FinTech has increased in the financial services industry, allowing financial intermediation by FinTech lenders remains controversial.[5] Regulators have argued that FinTech lenders require more regulation (Brooks and Calomiris, 2020); and lawmakers have been particularly concerned about whether FinTechs act in a more discriminatory way than traditional banks.[6] Yet FinTechs have argued that they are less discriminatory because they do not rely on relationships or face-to-face interactions with customers.[7] Given bank regulators' ongoing concerns on racial and income disparities in access to finance, our findings have implications for how FinTech expansion affects the small business lending market, where SBA-backed loans have material importance.

Our first question is whether FinTechs provided more access to PPP loans in areas where these loans were needed more. Traditional financial institutions (i.e., depository institutions) have been shown to be inefficient in their allocation of financial services across customers of different sizes, locations, and demographics (Philippon, 2015; Harvey et al., 2021). And, in the particular case of allocating PPP loans, banks have been heavily criticized by the popular media for favoring their relationship borrowers at the expense of smaller firms that were hit hardest by the pandemic.[8] Granja et al. (2020) show that during Phase 1 of the PPP program, banks did not allocate credit to regions where it was needed. We show that at this time, FinTech lenders provided more PPP loans than traditional banks to areas with a worse economic shock. Studying Phase 2 of the program leads to interesting findings as well: While both traditional banks and FinTech lenders provided more PPP loans to the areas with a higher COVID-19 case rate and more unemployment claims, the response of the FinTech lenders was about ten times larger.

Second, we study whether FinTech lenders provided PPP loans to businesses with limited previous access to the banking system relative to traditional banks. Survey evidence shows that minority-owned small businesses are less likely to access credit through a relationship with a bank and are less satisfied with the relationships they do have (Federal Reserve Bank of Atlanta Small Business Credit Survey, 2019). Minority-owned small businesses are also more reliant on SBA loans than white-owned businesses, even though pure FinTech lenders are currently not allowed to participate in this market. Comparing borrowers located in the same county, we show that borrowers in ZIP codes with few bank branches, lower incomes, and a larger non-white share of the population were more likely to get a loan from a FinTech lender. Moreover, relative to FinTech lenders, traditional banks provided a higher fraction of PPP loans to firms in industries with stronger ties to the banking system. Our findings show that banks base their PPP loans on past relationships, and they are geographically constrained by the location of their physical branches, unlike online FinTech lenders, where prior relationships are less relevant.

Third, we ask whether FinTech lenders "expand the pie" of financial services or merely redistribute it. Even for borrowers that could access traditional banks, FinTechs lenders may be quicker or more convenient, as Buchak et al. (2018) show for mortgage loans, especially during the early phases of the PPP program. To study whether small businesses substitute to FinTech lenders when local banks are less responsive to their demand for PPP loans, we use an approach that is akin to a shift-share ("Bartik") design to predict local bank responsiveness independent of the magnitude of the COVID-19 shock. We find that borrowers respond to a lack of bank PPP provision by somewhat substituting to FinTech lenders. But this substitution, which is significant statistically, is only about 27 percent of the decrease in traditional bank lending. Overall, we show that FinTech lenders expanded the access to the PPP program but did not fully close the gap in financial services across regions where banks operate.

It is important to note that the incentives in play for PPP loan origination are different from standard credit as PPP loans are potentially forgiven. Nevertheless, our results speak to the differences in the use of banking relationships — as measured by branch networks — and new technology to allocate government-backed credit, which is an important part of small business borrowing. Therefore, our findings have important implications for the potential effects of allowing (more) FinTech lenders to participate in any type of fully or partially-guaranteed government loan program (e.g., SBA 7a loans).[9] Allowing greater FinTech partic-

[4] According to Non-Federally Regulated Lender laws, FinTech lenders with a state banking license cannot participate in SBA's loan programs unless they partner with a qualifying bank.

[5] See, e.g., Buchak et al. (2018), Chernenko et al. (2019), Gopal and Schnabl (2020), Stulz (2019), Liebersohn (2020), and Gopal and Schnabl (2020).

[6] https://cleaver.house.gov/sites/cleaver.house.gov/files/Fintech_Report_1.pdf ; https://www.occ.treas.gov/news-issuances/news-releases/2020/nr-occ-2020-112.html as of March 2022.

[7] See https://www.fintechfutures.com/2020/03/can-fintech-eliminate-credit-discrimination/ as of March 2022.

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

[9] See, e.g., Craig et al. (2008) showing positive effects of SBA-backed loans on employment in low-income areas.

ipation has the potential to increase the efficiency of small business lending even during non-crisis periods.

2. Literature review

Recent literature investigates various aspects of the PPP program. Our paper is the first one to focus on how FinTech lenders affected financial access to PPP loans by small businesses in areas traditionally underserved by banks and for borrowers with few connections to banks. Our findings are also related to research on the differences between FinTech lenders and banks, and more broadly, on how non-bank lenders respond to shocks.

Our paper is most related to two recent complementary papers focusing on racial disparities in access to PPP loans. Chernenko and Scharfstein (2021) focus on the role of racial bias. They show that Black- and Hispanic-owned restaurants in Florida were significantly less likely than white-owned ones to get PPP loans, even controlling for bank networks. Howell et al. (2020) study the role of automation. They show that FinTech lending and switching to automated lending processes by traditional banks help increase access to the PPP loans by Black-owned businesses. Differently from these papers, our work focuses on how FinTech helped close the gap in access to PPP credit in areas with fewer bank branches and a larger share of the minority population. We contrast FinTechs with traditional banks, which rely on existing branch networks to supply PPP loans.

Several papers have focused on who received PPP loans, especially in the first few weeks of the program. While these papers include FinTechs in their sample alongside other lenders, most do not show that FinTechs behaved differently than banks, as we do. Li and Strahan (2020) focus on the role of close relationships with banks for accessing the PPP loans. Balyuk et al. (2021) also find that banking relationships matter: larger borrowers received the PPP funds early, and this preferential access by larger borrowers concentrates is most pronounced at top-10 banks. Cororaton and Rosen (2021) study public firms that got funding through the PPP and received significant media outrage as a result. Other papers have asked whether the program was effective at helping borrowers who needed it most. Granja et al. (2020) show that banks, in the first phase of the program, targeted regions that were less adversely affected by the pandemic and study its future employment effects.[10]

Our paper also contributes to the literature on the differences between non-bank lenders and traditional banks. Beyond the setting of the COVID-19 pandemic, several papers study loan supply following natural disasters. Morse (2011) shows that payday lenders facilitate access to finance following disasters, and Cortes and Strahan (2017) show that traditional banks reallocate capital across regions. To the best of our knowledge, there are no papers focusing on the disaster response of FinTechs in particular (and how it differs from banks). Beyond the setting of disasters, research on FinTechs has found that FinTech lenders process loan applications faster than traditional banks, improving the efficiency of financial intermediation in mortgage markets, but they do not necessarily serve underserved borrowers with low access to finance.[11] Gopal and Schnabl (2020) show the increasing importance of FinTech lending for small businesses, where the sample includes asset-backed loans to purchase durable goods. Unregulated finance companies have traditionally been key players in this market, and their role has increased even more after the 2008 Financial Crisis, as shown by the authors.[12] Balyuk et al. (2020) study commercial loans through online lending platforms and show the importance of banking relationships for small businesses. In a setting where there is no credit assessment based on soft information, we find that FinTech lenders reach a wider borrower base while banks remain constrained within their branch networks. Ours is the first paper to focus on how FinTechs can provide financial services to small businesses in underserved areas, including neighborhoods with a high share of the minority population and low median incomes.

Beyond the PPP program, our findings on “expanding the pie” of access to PPP loans contribute to the literature on financial inclusion. This literature has mostly focused on households, but a few papers have also studied small businesses in minority and low-income neighborhoods.[13] Begley et al. (2020) and Chatterji and Seamans (2012) show how different types of regulations — on SBA loans and on credit cards — can hinder financial access for minority-owned small businesses. We focus on a different source of credit than these papers, but like these papers, we find that deregulating credit supply has the greatest impact on borrowers with poor access to the traditional banking system.

3. Payroll protection program and data

The Paycheck Protection Program (PPP) in 2020 authorized up to $669 billion toward job retention by small businesses with 500 or fewer employees.[14] The program pro-

[10] 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, 2021; Fahlenbrach et al., 2020; Pastor and Vorsatz, 2020; Halling et al., 2020; Falato et al., 2021; Bartik et al., 2020; Faulkender et al., 2020; Lynch, 2021).

[11] There is also a growing literature on online, peer-to-peer, unsecured personal loans (see, e.g., Morse, 2015, for a review; de Roure et al., 2018; Di Maggio and Yao, 2021; Tang, 2019; Vallee and Zeng, 2019; Basten and Ongena, 2020; Carlin et al., 2020, for more recent papers).

[12] See, also, Hanson et al. (2015); Butler et al. (2016); Cole et al. (2019); Cortes et al. (2020); Mills and Dang (2021), and Chernenko et al. (2019) showing how various nonbank lenders have been filling the gap when large commercial banks faced regulatory constraints and, therefore, had to pull back from commercial lending.

[13] Recent research on household financial inclusion in the U.S. context include Calzada et al. (2019); Brown et al. (2019); Célerier and Matray (2019); Buchak and Jørring (2016); Stein and Yannelis (2020); Bartlett et al. (2022), and Fuster et al. (2021). A number of papers study the effects of improved financial access in developing countries, including for small- and medium-sized enterprises (see Barajas et al., 2020, for a review of this literature).

[14] Funds were distributed in three phases. $342 billion was distributed in Phase 1 over April 3–16, 2020. Then, after a short break, Phase 2 ran over April 26-August 8, 2020, by which time $525 billion had been distributed. Additional funds for a third phase were authorized in 2021, and as of May 31, 2021, a total of 278 billion had been distributed in 2021.

vided loans to small businesses and eligible nonprofit organizations to pay up to eight weeks of their payroll costs, including benefits, interest on mortgages, rent, or utilities.[15] With about $525 billion approved — over 5.1 million loans passed through 5460 financial institutions— by August 8, the PPP was one of the largest economic stimulus programs in U.S. history. According to data reported by program participants, it supported over 51 million jobs, a majority of small business employment in the United States.

The program was administered by the Small Business Administration (SBA), but loans were allocated through eligible financial institutions. Eligible institutions included any SBA 7(a) lender, federally insured depository institution or credit union, or any other lender that was approved by the SBA and enrolled in the program. Lenders neither charged any fees nor asked for collateral to grant these small business loans. Loans originated prior to June 5 had a maturity of 2 years, while those originated after June 5 had a maturity of 5 years. PPP loans carried an interest rate of 1%, but loan repayment was deferred for six months. There was no fee charged to the borrowers but lenders received a fee income of 5% for loans up to $350,000, 3% for loans between $350,000 and $2,000,000, and 1% for loans above $2,000,000, paid by the SBA. Most importantly, PPP loans were fully forgiven if the funds were used at least 60% for 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 $102,697.

Note that our sample period covers the first two phases of the Paycheck Protection Program, which ended on August 8, 2020. Since then, the new Biden administration administered another phase (Phase 3) of the program, which was dominated in volume (75%) by second draws of PPP loans by certain eligible businesses, allocating only about $69 billion dollars of loans to first-time PPP borrowers (see Appendix Table A.1). Excluding second-draw loans, over 80% of the lending volume from the entire program was approved by May 1, 2020, and 88% by August 8, 2020, when Phase 2 — and our sample period — ended. We exclude Phase 3 loans from our sample due to various changes in the program, like the opportunity for second draws by only a subset of borrowers. The most important of these changes was a special 14-day period, during which only businesses with fewer than 20 employees could apply to the PPP loan program. Note that, consistent with our findings and ensuring-equity purpose of the new phase, the percentage of FinTech lenders more than doubled in Phase 3 while the number of loans extended by them almost quadrupled.[16]

3.1. Data and definition of FinTech

Our main data source is the database of PPP loans released by the Small Business Administration (SBA). It consists of loan-level data on all PPP loans that were approved by the SBA. The data include some characteristics of borrowers and loans. The borrower's ZIP code is included, and 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.[17]

We match this loan-level data to bank identifiers from the Federal Financial Institutions Examination Council (FFIEC) using the lender names provided.[18] Most lender names can be matched automatically.[19] Lenders which we are not able to match automatically we match by hand. For the deposit-taking banks, we obtain 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.

We identify Fintech lenders as any unregulated nonbank lender as well as any regulated online bank with a FinTech focus. Specifically, nonbank lenders are nondepository financial institutions, like Kabbage, Inc., that generally rely on FinTech in their lending.[20] 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 only one administrative branch. They also rely heavily on technology for both their lending and deposit taking. Therefore, we classify banks in our sample as online banks if they extensively operate online with one administrative branch only. To this sample, we also add a few banks with more than one branch, as identified by Abrams (2019) as online FinTech banks. A few examples of these additions are Axos Bank, Capital One Bank, and the TIAA Bank. A full list of our online bank FinTech lenders is provided in the Appendix Table B.2. Note that online banks in our sample often partner with independent nonbank FinTech lenders (e.g., WebBank partnering with PayPal), but they may also originate loans directly (e.g., Axos Bank). The top three online banks, Cross River Bank, Celtic Bank, and WebBank, extended more than 90% of the online-bank PPP loans with 192,652, 146,792, and 75,837 loans, respectively; and, they all partnered with nonbank FinTechs.

Our main measure of FinTech lenders combines online banks with nonbank lenders, but, in Appendix Table A.2, we also provide our main results for these subgroups of institutions since their regulatory treatment is different.

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

[16] https://www.sba.gov/funding-programs/loans/covid-19-relief-options/paycheck-protection-program/ppp-data as of March 2022.

[17] 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.

[18] Specifically, we use the Attributes File from the end of June, 2020. Note that bank lending includes some lending by credit unions and saving institutions, which are also depository institutions.

[19] 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.

[20] Some nonbank lenders in the sample may not necessarily be traditional FinTechs (such as Business Development Corporations), but most are. See Appendix Table B.1 for the largest nonbank lenders in our sample.

Moreover, for robustness, we use an alternative definition of FinTech lenders, as identified by the SBA itself as of May 8, the last day of our sample period.[21] To this list, we add the list of regulated banks that FinTechs partnered with, as some nonbank FinTech lenders extended their PPP loans directly while some others worked through their regulated online bank partners.[22] We hand-collected data on these partnerships from lender websites. In this way, we identified bank partners for all FinTech lenders except for two: Lendio and NAV that run marketplace lending platforms. Lendio, for example, states on its website that they have over 50 lending institutions. Including these institutions in the traditional banking sample, rather than the Fintech sample, would only weaken our results. Lenders identified as FinTechs in this way are presented in Appendix Table B.3.

We match this data to demographic information from the 2000 Decennial Census and the 2014–2018 American Community Survey (ACS) (Manson et al., 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 re-code 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 establishments — i.e., the number and size of eligible establishments— in each ZIP code, we use data from ZIP Business Patterns 2018 data on the number of establishments with fewer than 500 employees. The average size of eligible establishments is calculated as the total employment divided by the number of establishments in each ZIP code.

We measure the magnitude of the economic shock by county using data from the Opportunity Insights *Track the Recovery* web site (Chetty et al., 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 daily count of COVID cases by county in March 2020 per 100 people. See Chetty et al. (2020) for more details on these measures.

To compare cross-industry use of different aid programs, we use the Small Business Pulse Survey (SBPS) from the U.S. Census Bureau (see, e.g., Buffington et al., 2020). The SBPS is a survey of small business performance, program use, and economic expectations administered on a weekly basis beginning in late April 2020. The data for this survey is released on an aggregated basis for each week. We use a version of the survey compiled by NAICS 3-digit industry code.

3.2. Summary statistics

Summary statistics by ZIP codes, weighted by PPP loans, are shown in Panel A of Table 1.[23] The mean (median) ZIP code had 620 (508) PPP loans. In the ZIP codes in our sample, 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 the average ZIP code with PPP loans, there are 9.5 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 939 eligible establishments and a total population of 13,729, on average. These areas also had 0.02% March COVID case rate and 3.35% unemployment growth.[24]

Panel B of Table 1 shows summary statistics for the loans themselves. 15% of loans in the sample come from a FinTech lender, of which 6% are from nonbanks and 9% are from online banks. FinTech PPP loans are, on average, smaller than loans from traditional banks: They have a median size of $15,835, whereas loans from traditional banks have a median size of about $27,331. They also support fewer (median of 1 versus 4; mean of 5 versus 13) jobs, suggesting that they go to smaller businesses.

The summary statistics shown in Appendix Table A.4 reveal that FinTech loans were more likely to go to hard-hit ZIP codes and industries, as well as to smaller businesses. It is plausible that firms in more technology-enabled industries, such as IT and services, are more likely to use FinTech for their PPP loans. Appendix Fig. A.1 shows the fraction of FinTech loans in each 2-digit NAICS industry, where there is no evidence for such a pattern. Industries and ZIP codes in the bottom quintile of economic performance had about 22% of loans coming from FinTech, compared to 15% for the national average. In the smallest quintile of loans, 24% come from FinTechs. Small businesses are also more likely to get their loans from FinTechs.

3.3. Empirical strategy

Our goal is to compare how FinTechs and traditional banks provide PPP loans to borrowers with weak connections to the banking system and in areas with few bank branches. In general, differences in PPP loan provision could be due to loan supply (e.g., banks may be unwilling to lend far from their branches) or due to loan demand (e.g., due to differences in the economic shock across regions or types of borrowers). We are primarily interested in the effects of loan supply.

One way to measure supply would be using a data set such as the one in Buchak et al. (2018), which includes information about both loan applications and loan acceptance rates, matched into information about the applicants themselves. Conditional on applicant characteristics, the acceptance rate could tell us about the sup-

[21] https://www.sba.gov/sites/default/files/2020-05/Fintech_Companies_Participating_in_PPP_05.08.20_0.pdf as of March 2022.

[22] As Stulz (2019) discusses, many purely online FinTech lenders (e.g., Kabbage), which started as peer-to-peer lenders extending only personal loans, have also moved to direct small-business lending over time, through a banking subsidiary or a funding bank partner. The top nonbank PPP lender, Kabbage, for example, not only extended 160,897 PPP loans directly, but also partnered with Cross River Bank, which extended another 192,652 PPP loans by the end of Phase 2.

[23] See Appendix Table A.3 for unweighted statistics.

[24] Unemployment rates, which we can measure only at the county level, are not available everywhere.

Table 1
Summary statistics.

	Mean	Std. Dev	Median	Count
	a. ZIP Code-Level			
Frac Nonbank	0.06	0.05	0.05	36,267
Frac Online Bk	0.09	0.07	0.08	36,267
Total FinTech PPP Fraction	0.15	0.11	0.14	36,267
Frac Bk/CU	0.85	0.11	0.86	36,267
Num. PPP Lns	620.28	528.45	508.00	36,267
Median Income	70,653.10	29,866.70	64,091.00	29,736
Frac. 45 m + Commute	0.17	0.10	0.14	30,857
Frac. White	0.74	0.21	0.80	31,160
Population	13,728.85	9,082.21	12,730.00	31,223
Num. Bk Branches	9.46	7.23	8.00	19,369
COVID Case Rate	0.02	0.04	0.00	35,355
Unemp. Growth	3.35	1.82	3.01	17,097
Num. Estabs	939.28	785.13	785.00	33,571
	b. Loan-Level			
FinTech Indicator	0.15	0.36	0	5,114,448
Non-bank Indicator	0.063	0.24	0	5,114,448
Online Bk Indicator	0.089	0.28	0	5,114,448
Single Person	0.33	0.47	0	5,114,448
Jobs (All)	12	33	4	5,114,379
Jobs (Traditional)	13	35	4	4,339,037
Jobs (FinTech)	5	16	1	775,342
Amount (All)	102,697	353,776	23,125	5,114,379
Amount (Traditional)	113,803	376,543	27,331	4,339,037
Amount (FinTech)	40,545	166,000	15,835	775,342

Panel a presents ZIP-code level summary statistics, weighted by PPP loans per zip code; and, Panel b presents loan-level summary statistics. See Appendix C for variable definitions. Bank branches are for ZIP codes that have at least one branch. Unemployment data is not available for all regions. Data sources: SBA PPP database, FDIC Summary of Deposits database, Decennial Census/ACS, County Business Patterns.

ply of loans by both types of lenders. The SBA does not provide data on loan applications. Therefore, we approximate the ideal experiment by adjusting for differences in the overall level of PPP demand. Most importantly, our main dependent variable is the *fraction* of PPP loans originated by FinTechs, measured relative to the overall number of PPP loans in a given ZIP code. In areas where general PPP demand is greater due to worse economic conditions, there would be more PPP loans, but the fraction of PPP loans from FinTechs would not necessarily be higher. Furthermore, to control for county-level differences in PPP loan demand, our main estimates are identified by variation across ZIP codes or borrowers located within the same county. We accomplish this by including county (or county-by-industry) fixed effects in our regression specifications.

Our main assumption is, therefore, that borrowers with weaker links to the banking system — for example, businesses located in ZIP codes with few branches — do not have a latent preference for FinTechs relative to other borrowers in the same county. An important way our assumption could fail is if borrowers with weak banking ties have better internet or computer access and prefer FinTechs for that reason. Yet if anything, we find that good internet access is correlated to *weak* access to the banking system, and that controlling for technology-related variables strengthens our results. We also show that substitution between the PPP program and other government aid programs is not related to the fraction of PPP loans coming from FinTech.

Our main analyses are either at the ZIP code level or at the loan level. To ensure that ZIP and loan-level analyses are consistent with each other, we weight ZIP level analyses by the number of observations per ZIP code.[25] In our ZIP-code level regression specifications, we measure the fraction of FinTech and bank lending in each ZIP code. We study variables that vary by ZIP code (such as the number of branches), so we cluster standard errors by ZIP code in the loan-level analysis and use robust standard errors for analysis that already uses ZIP codes as the unit of analysis.

Finally, one of our main questions is whether FinTechs expand access to the financial system or merely replace existing banks. To answer this question, we measure the degree of substitution between banks and FinTechs using a Bartik-style loan supply shock that is independent demand shifters. Section 6 describes the construction of this shock and presents the results.

4. The geography of FinTech lending

Fig. 1 shows the number of PPP loans by week between April 3, when the first Phase of the PPP started, and August 8, when the second Phase of the PPP ended.[26] The *X*-axis of this figure shows the approval week and the *Y*-axis

[25] Unweighted ZIP level analyses are very similar to weighted ones, but we prefer the weighted estimates to create consistency throughout the paper.

[26] The PPP's second phase was originally scheduled to end on June 30, but then it resumed on July 6, and ended on August 8.

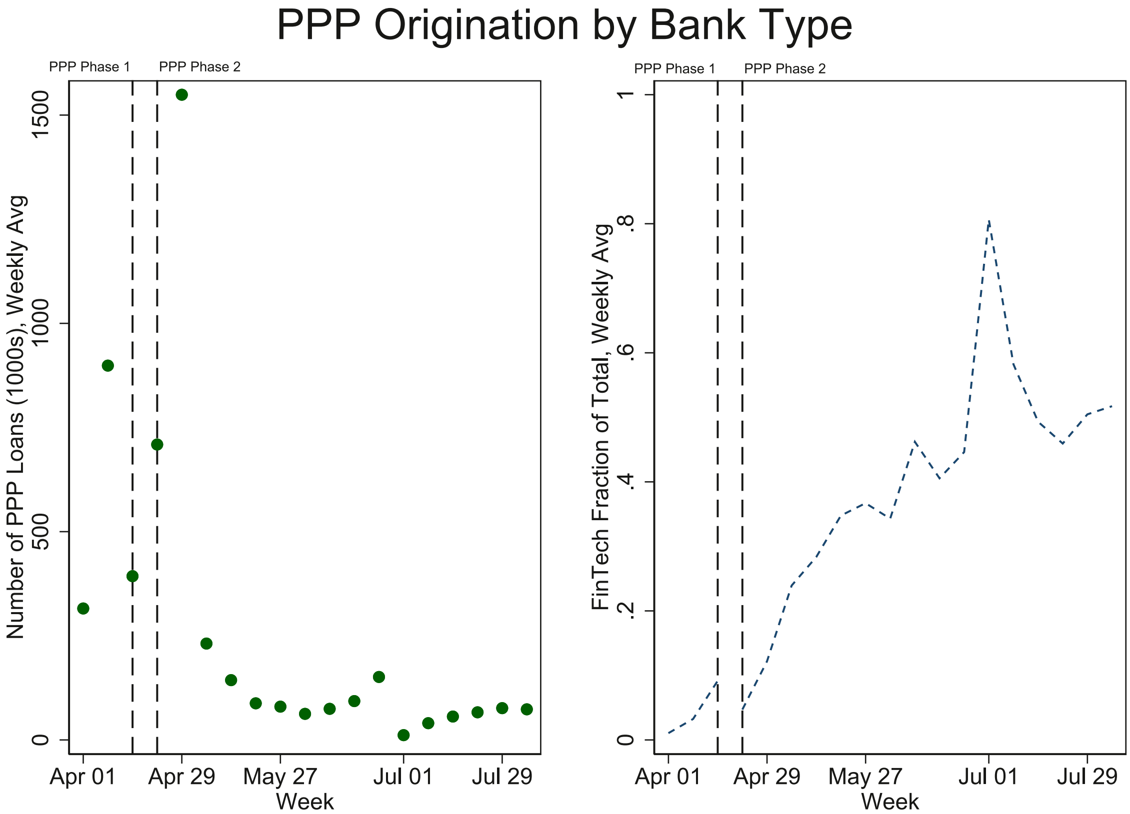

Fig. 1. The figure shows the number of PPP loans by approval week between April 3 and August 8, 2020. There is a gap between April 16, when PPP Phase 1 ended, and April 27, when Phase 2 began. Data source: SBA PPP Loan Database.

shows the number of PPP loans approved. There is a gap between April 16, when PPP Phase 1 ended, and April 27, when Phase 2 began. There is also a spike in the number of PPP loans during the first days of Phase 2, which reflects the delayed response to applications made between the two phases.

The right panel of Fig. 1 presents the average FinTech fraction of PPP loans by week. The share of loans from FinTech institutions started increasing during the last few days of Phase 1 and significantly accelerated during Phase 2, reaching the majority of overall lending in terms of number of loans. When we consider the volume of loans instead, shown in Fig. A.2, the share of FinTech is unsurprisingly smaller in comparison to the share of traditional loans, especially in Phase 1. However, this finding is consistent with FinTechs specializing granting large number of small loans to small borrowers, which are the main targets of the PPP.

We begin by studying where, on a national basis, FinTech lenders were more widely used relative to traditional banks.[27] Table 2 investigates whether FinTech PPP loans flowed unconditionally to the areas that needed it most in both periods, and if they differed in this regard from traditional banks. 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. Here and throughout the paper, we control for the log number of eligible establishments by ZIP code to absorb variation in PPP lending due to differences in the number of establishments across regions.

During Phase 1, traditional banks did not provide PPP financing to the regions with higher case rates or higher unemployment, as already found by Granja et al. (2020). Did FinTechs do any better in Phase 1? The dependent variable in Column 1 is the fraction of PPP loans coming from FinTech lenders during both phases. The FinTech share is higher in areas with a worse economic shock using both

[27] We use an independent measure of regional interest in online PPP lending based on Google searches to validate our measure. 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. The top state for online searches is Georgia, where the largest nonbank FinTech lender in the sample, Kabbage, Inc., is based. Appendix Fig. A.3 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. This finding is supported by information we learned from discussions with FinTech lenders, that Google searches were an important way that small businesses found out about FinTech loans.

Table 2
Geographic correlates of PPP provision.

	(1) FinTech PPP Frac.	(2) Log PPP FinTech Phase 1	(3) Log PPP Trad. Bk Phase 1	(4) Log PPP Local Bk Phase 1	(5) Log PPP FinTech Phase 2	(6) Log PPP Trad. Bk Phase 2	(7) Log PPP Local Bk Phase 2
COVID Case Rate	0.81***	0.016	−4.07***	−2.90***	4.72***	0.48***	0.60***
	(0.045)	(0.26)	(0.23)	(0.33)	(0.19)	(0.080)	(0.15)
Unemp. Chg	0.016***	0.057***	−0.070***	−0.14***	0.13***	0.028***	0.016***
	(0.0013)	(0.0072)	(0.0056)	(0.013)	(0.0084)	(0.0023)	(0.0045)
Log Establishments	0.012***	1.04***	0.89***	0.98***	1.08***	0.96***	1.23***
	(0.0011)	(0.015)	(0.0066)	(0.017)	(0.0087)	(0.0033)	(0.0076)
Observations	16,110	6269	14,669	7747	10,658	15,540	8219
R^2	0.276	0.558	0.747	0.382	0.723	0.917	0.777

ZIP code level regression specifications showing the relationship between COVID-19 shock and the degree of PPP origination, for traditional banks and for FinTech lenders. “Local Banks” are traditional banks, where the sample of PPP loans is limited to those coming from a bank that has a branch in the same ZIP code as the PPP loan. Estimates are weighted by PPP loans per ZIP code. Robust standard errors are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Data sources: Chetty et al. (2020) SBA PPP loan database, and the 2014–2018 American Community Survey. See Appendix C for variable definitions.

measures of the shock. Next, we ask whether this relationship is because more FinTech loans are going to areas with a worse shock, or because fewer traditional bank loans are going to these areas. To do this decomposition, we estimate specifications where the dependent variable is the log of total PPP loans by traditional banks or by FinTech lenders, and we split the results by program phase.

Column 3 of Table 2 shows that traditional banks provided *fewer* PPP loans to counties that needed it more during Phase 1 of the program. 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)). According to the coefficients in Columns (2) and (3), each additional COVID case per 100 people was associated with 4 log-points less PPP lending from traditional banks but no less from FinTech lenders. One more percentage point increase in unemployment was associated with 0.07 log points less traditional bank lending and 0.06 log points more FinTech lending. However, an important caveat to FinTech's greater lending in hard-hit areas is that top FinTech lenders did not get approval till the last week of Phase 1 and, therefore, they were responsible for only a small part of lending during Phase 1 overall.

One possible explanation for the failure of traditional banks in reaching the areas hit more by the COVID-19 shock during Phase 1 could be their ability or preference to start PPP lending in areas with bank branches. If areas underserved by bank branches were also hit worse, we would find the findings presented in Column (3) troubling, given the intention of the PPP to reach worse-hit businesses as quickly as possible, but not surprising. In Column (4), we limit the sample of PPP loans to those extended by traditional banks that have at least one branch in the same ZIP code as the PPP loans, and hence focus on lending by *local* traditional banks. The findings are similar and even larger economically: even local banks with close-by branches did not provide PPP financing to the regions with higher case rates or higher unemployment during Phase 1 of the PPP.

Another possible reason that traditional banks did not lend more in the worst-hit areas may be that they faced different incentives than FinTech firms, for example, because stricter anti-money-laundering compliance made it more expensive for traditional banks to acquire new customers than FinTechs. However, many regulated banks partnered with FinTech firms to originate PPP loans for their commercial banking customers, suggesting that they wanted to originate PPP loans quickly but did not have the capacity to do so themselves. These traditional banks may have faced internal barriers to adopting new technologies even when they were motivated to do so. Moreover, the PPP program could be more appealing to certain types of banks. For example, Li and Strahan (2020) argue that the program terms were likely more appealing to smaller banks, as they specialize in small business lending unlike large banks and partly as large banks focused on the loan demand from their large customers, initially, during the last weeks of March. Lastly, there is also some evidence that liquidity constraints on banks might have led to their aversion in PPP lending. As Anbil et al. (2021) show commercial banks that used the Paycheck Protection Program Liquidity Facility (PPPLF) of the Federal Reserve extended significantly larger fraction of their assets as PPP loans, compared with the banks that have not used this liquidity support.

During Phase 2, as shown in the last three 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 needs than traditional banks were. The coefficient on the average case rate is about ten times larger for FinTech loans than traditional bank loans. During Phase 2, each additional COVID case per 100 people was associated with 4.7 log points more FinTech loans and 0.48 log points more loans from traditional banks. In Column 7, where we concentrate on the traditional local banks, the difference drops but only slightly, with the order of magnitude of almost ten times smaller than the FinTech lenders' response.

4.1. Demographics of FinTech loans

Fig. 2 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 vis-

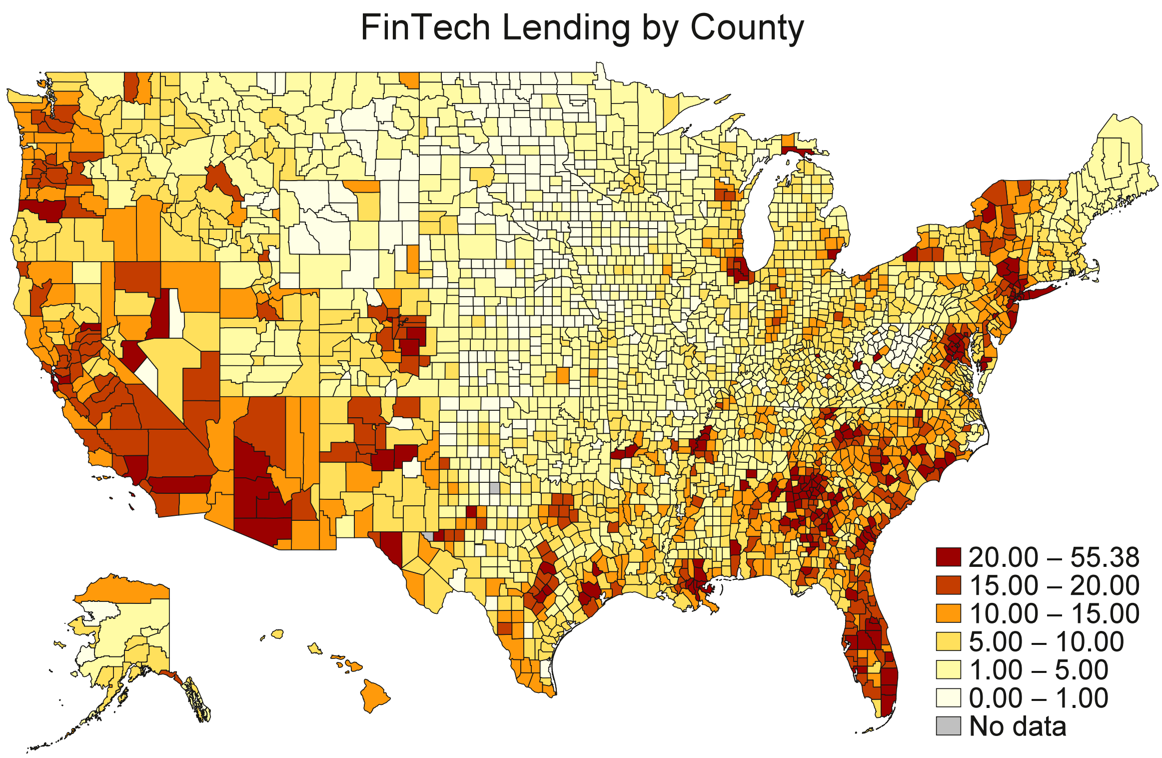

Fig. 2. This figure shows the country-level graph of the fraction of PPP Loans from FinTech Lenders across U.S. Counties. Colors correspond to bins of the percentage of all PPP loans coming from FinTech lenders. Data source: SBA PPP database.

ible in this figure. Major metropolitan areas, such as 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. Appendix Fig. A.4 shows that these patterns are robust to scaling PPP lending by the percent of the national FinTech total, or the fraction of eligible establishments.

Our main question is whether FinTech lenders provided PPP loans to borrowers poorly-served by the banking system. The literature on banking has established that banks constrain their lending to be around their bank branches (Petersen and Rajan, 1994). Therefore, areas with many traditional bank branches are likely to be well-served by the traditional banking system, possibly reducing demand for FinTech loans instead.

At a descriptive level, the national data suggest that FinTech loans were most common in areas that are already well-served by the banking system: coasts and major metro areas. However, there may be other important factors that vary by state or county, such as differences in COVID-19 awareness or differences in historical FinTech marketing, that make this national figure hard to interpret. Therefore, our next step will be to study differences in FinTech PPP lending by borrowers located in the same county in order to control for these sorts of regional differences.

To motivate our within-county analysis, Fig. 3 shows the distribution of PPP loans for ZIP codes in Cook County, which includes most of the Chicago metro population, as an example. 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. The right panel of Fig. 3 shows the fraction of PPP loans that we classify as coming from FinTechs. Businesses in the richer ZIP codes of Chicago mostly get their loans from traditional banks, 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.

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.

5. Bank branch density and FinTech lending

A large body of research in banking shows that banks are more likely to have a lending relationship with borrowers located physically close to their branches and small business lending is generally local (see, e.g., Berger et al., 2005; Agarwal and Hauswald, 2010; Brevoort et al., 2010; Nguyen, 2019). Therefore, ZIP codes with more bank branches are known to have more competitive

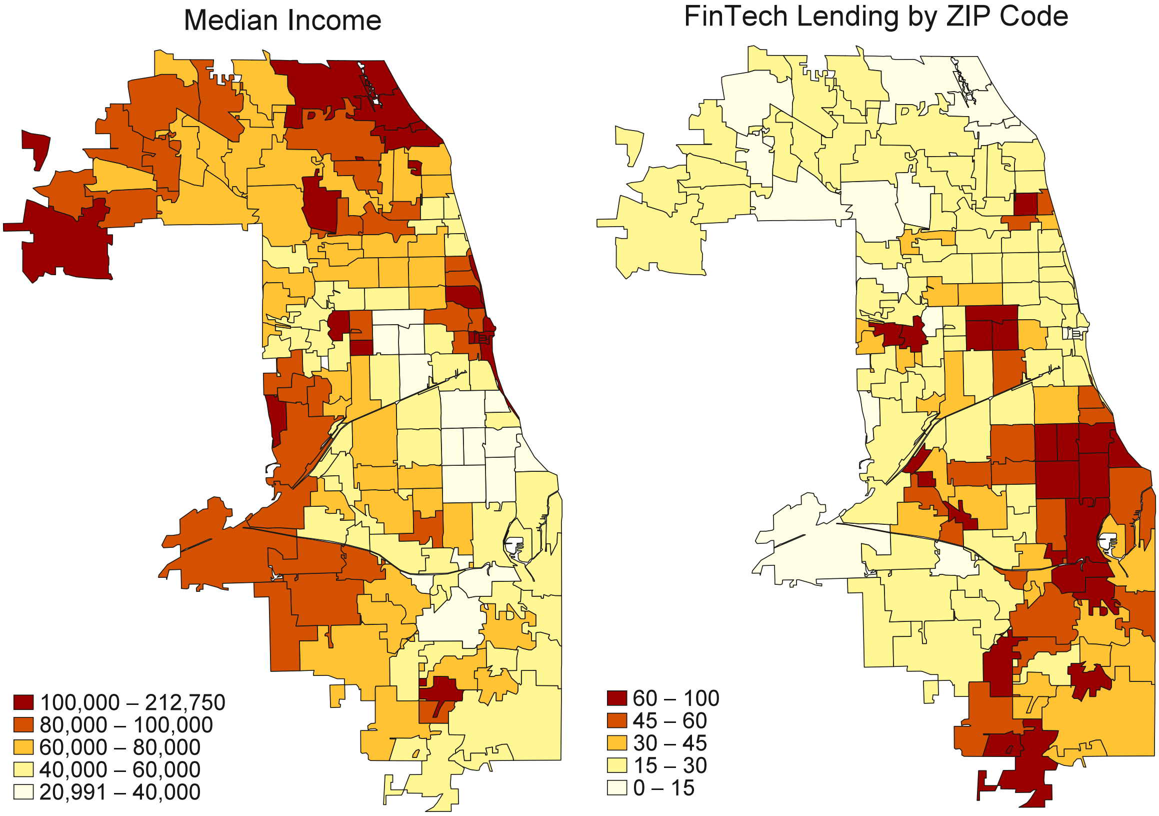

Fig. 3. This figure shows data from Cook County (Chicago Metropolitan Area) ZIP Codes. The right panel shows median incomes by ZIP code. The right panel shows the fraction of PPP Loans from FinTech Lenders. Data source: SBA PPP database.

banking markets and hence better credit access. Focusing specifically on the COVID-19 pandemic, Li and Strahan (2020) found that relationships continue to matter for PPP loans and credit access throughout the crisis. These facts motivate us to investigate the relationship between bank branch density at the ZIP code level and the types of PPP loans which are originated.

The relationship between bank branches and FinTech lending is shown in Fig. 4, which is a binscatter plot. The left panel of this figure, labeled "National", uses pooled ZIP code data from the entire country without fixed effects or controls. On the X-axis, we show the average (log) bank branches per ZIP code, where ZIP codes are grouped into ventiles and the logarithms are in base-10 to make interpretation simpler. The *Y* axis shows the fraction of Fintech PPP loans for each ventile. Based on the national patterns shown in Fig. 2, 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 Fig. 4 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 bank branches 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. If banks prioritized PPP lending to customers with existing bank relationships, we would expect to see a correlation between the number of bank branches and the likelihood that borrowers got their PPP loans from a traditional bank, controlling for plausible demand-side factors. We start with the following regression specification:

$$FinTechShare_{zc} = \beta_1 Branches_z + \delta_c + \varepsilon_z$$

where z indexes ZIP codes, c indexes counties, and δ_c are county fixed effects. We are primarily interested in β_1, the coefficient on the number of bank branches. Table 3 shows estimates of this specification which confirm the pattern in Fig. 4. Bivariate fixed-effects regressions, shown in Columns (1) and (2), show an economically and statistically significant effect of bank branches on FinTech lending. 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%, 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. The standard deviation of log branches is 0.85, so

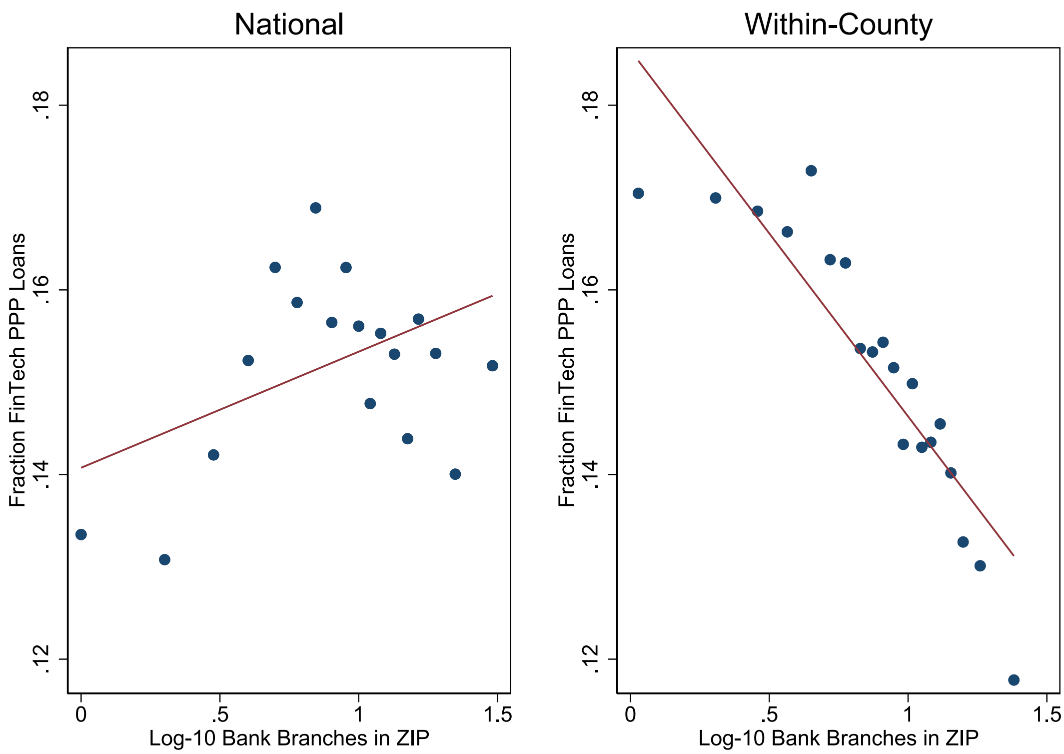

Fig. 4. These binscatter plots show how FinTech PPP lending varies with bank branch density. On the *X*-axis, we have the average (log) bank branches per ZIP code, where ZIP codes are grouped into ventiles and the logarithms are in base-10 to make interpretation simpler. On the *Y* axis, we have the fraction of Fintech PPP loans for each ventile, weighted by PPP loans per ZIP code. The left panel of the figure uses pooled ZIP code data from the entire country while the right panel presents within-country variation. Data sources: FDIC Summary of Deposits database and SBA PPP database.

Table 3
Bank branch density and fraction of FinTech loans.

	(1) FinTech PPP Fraction	(2) FinTech PPP Fraction (Alt Defn)	(3) FinTech PPP Fraction	(4) FinTech PPP Fraction (Alt Defn)
Log Branches	−0.017***	−0.016***	−0.020***	−0.019***
	(0.00094)	(0.00090)	(0.0012)	(0.0011)
Log Med. Inc			−0.017***	−0.018***
			(0.0032)	(0.0031)
Frac Commute 45+m			0.14***	0.14***
			(0.013)	(0.012)
Frac White			−0.17***	−0.15***
			(0.0082)	(0.0079)
Log Population			0.026***	0.026***
			(0.0011)	(0.0010)
Establishments Per Cap.			−0.00020	−0.00045
			(0.0036)	(0.0033)
Frac Estabs <10 Emp			0.17***	0.16***
			(0.010)	(0.0098)
Frac Estabs <500 Emp			−0.16***	−0.16***
			(0.0099)	(0.0093)
Observations	35,543	35,543	28,577	28,577
R^2	0.695	0.663	0.807	0.786
County FEs	X	X	X	X

This table presents ZIP-code level regression specifications showing the relationship between the share of FinTech PPP lending and the number of bank branches per ZIP code. Columns 2 and 4 use narrower definitions of FinTech lenders. See Appendix B for details on lender classification. Columns (3) and (4) have fewer observations because data on income and establishments is not available for all regions. Estimates are weighted by PPP loans per ZIP code. Standard errors are clustered by ZIP code. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Data sources: Chetty et al. (2020) and SBA PPP loan database. See Appendix C for variable definitions.

one standard deviation change increases the FinTech share by about 11% of the median.

The finding in Table 3 controls for county fixed effects, which eliminates many potential confounding variables that might vary by region. Nonetheless, we might worry that the relationship between bank branches and traditional bank lending is due to omitted demand factors, such as the types of businesses located there, rather than due to the supply of loans from traditional banks. Yet, adding local demographic and income controls slightly increases the estimated relationship between bank branches and the FinTech share of borrowers. In Columns (3) and (4), we add 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 0.017 to 0.020. FinTech lenders, therefore, reached not only to areas more severely hit by the virus, but also to under-served borrowers with limited access to the banking system.

As we noted in Section 3, FinTech lenders serve smaller borrowers than traditional banks do. If establishments in regions with fewer bank branches tend to be small, then part of the difference in PPP lending between banked and under-banked areas could be due to differences in borrower size composition between these areas. To test this hypothesis, we add controls for (a) the fraction of establishments in an area with fewer than 10 employees (i.e., very small establishments) and (b) the fraction with fewer than 500 employees (i.e., the fraction of all establishments that are eligible for PPP). The coefficient on the former variable is positive and large (0.17), suggesting that having many small establishments is indeed an important driver of FinTech PPP usage. However, we do not think this effect confounds the relationship between bank branches and FinTech PPP use, since including these variables does not affect the coefficient on bank branches.[28]

Table 4 shows results from similar specifications at the *loan* level. The main advantage of estimating specifications at the loan level is that we can compare loans from borrowers in the same industry in the same county, but located in ZIP codes with a different number of local bank branches. By including industry-by-county fixed effects in the regression specifications, the estimates are identified by differences in the number of branches for borrowers in the same industry and the same county but located in different ZIP codes. Estimates with county fixed effects alone (in Column 1) are of a similar magnitude to those with interacted county-by-industry effects (shown in Column 2). We also separate these specifications for small loans (with loan size below \$350,000) and larger ones (with loan size above \$350,000) and show the results are quite similar. These loan categories are potentially relevant because lenders were paid less to originate loans in the former category, which might have affected FinTechs lenders' incentives to originate PPP loans, relative to banks' monetary incentives.

5.1. Elasticity of banks' PPP loan supply

We also exploit variation in PPP demand coming from regional variation in the COVID-19 shock to show that, relative to FinTechs, banks' supply of PPP loans is more elastic in regions where there are more branches. To test this prediction, we interact the magnitude of the shock with the density of bank branches and study the supply response by FinTechs versus by banks. We use the following regression specification:

$$FinTechShare_{zc} = \beta_1 Branches_z + \beta_2 Shock_c \times Branches_z + \delta_c + \varepsilon_z$$

where z indexes ZIP codes, c indexes counties, and δ_c are county fixed effects.[29] We now focus on β_2, the coefficient on interaction between the COVID-19 shock and the number of bank branches. We expect that a high shock provokes a greater response by banks relative to FinTechs in areas with many bank branches. Therefore, we expect β_2 to be negative. We again measure the COVID-19 shock using both the number of cases per 100 people in March and the rise in unemployment at the county level between the months of March and April.

The results are shown in Table 5, 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 Column (2)). Interpreting the coefficients in the first two columns, one more case per 1000 people means that FinTechs originate about 8 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 1000 from about 8 percentage points to about 7 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 1.6 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 1.1 percentage points. Overall, these results show that banks' supply of PPP loans was more elastic in regions with more branches, highlighting again the importance of branch networks for banks' provision of financial services.

Borrowers in low-income regions learned about the PPP program from a variety of sources, including messaging from their regular banks and from public service announcements from the SBA and nonprofits.[30] Informal discussions with FinTech lenders suggest two important ways

[28] In Appendix Table A.5, we show that our results are robust to using PPP loan data from Phase 3, as well. In the same table, we also include a specification for second-draw loans only and find similar results.

[29] Since the COVID-19 shock is measured at the county level, county fixed effects mean we do not include a main effect for the COVID shock in the baseline specification.

Table 4
Bank branch density and fraction of FinTech loans, loan level estimates.

	(1) FinTech PPP Fraction	(2) FinTech PPP Fraction	(3) FinTech PPP Fraction Below $350,000	(4) FinTech PPP Fraction Above $350,000
Log Branches	−0.020***	−0.016***	−0.016***	−0.0019*
	(0.0011)	(0.00081)	(0.00084)	(0.0010)
Log Med. Inc	−0.017***	−0.015***	−0.016***	−0.00038
	(0.0030)	(0.0022)	(0.0022)	(0.0026)
Frac Commute 45+m	0.14***	0.10***	0.097***	0.035***
	(0.012)	(0.0091)	(0.0091)	(0.014)
Frac White	−0.17***	−0.13***	−0.14***	−0.016***
	(0.0078)	(0.0053)	(0.0054)	(0.0059)
Log Population	0.026***	0.018***	0.017***	0.00031
	(0.0010)	(0.00076)	(0.00077)	(0.0011)
Establishments Per Cap.	−0.00022	0.00027	0.00034	−0.000014
	(0.0034)	(0.0021)	(0.0022)	(0.0013)
Frac Estabs <10 Emp	0.17***	0.11***	0.091***	0.025**
	(0.0098)	(0.0072)	(0.0074)	(0.010)
Frac Estabs <500 Emp	−0.16***	−0.12***	−0.10***	−0.046
	(0.0093)	(0.0074)	(0.0075)	(0.028)
Observations	5,016,900	4,594,345	4,326,497	199,762
R^2	0.072	0.247	0.250	0.270
County FEs	X			
County X NAICS FEs		X	X	X

This table presents loan-level regression specifications showing the relationship between the likelihood that a PPP loan is from a FinTech lender and ZIP-code level statistics, including the log number of bank branches. Columns (3) and (4) use data from PPP loans with an initial approval amount below and above $350,000 respectively. Robust standard errors are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Data sources: SBA PPP loan database, ZIP Business Patterns, the 2014–2018 ACS and the 2010 Decennial Census. See Appendix C for all variable definitions.

Table 5
Increases in county unemployment and PPP origination.

	(1) FinTech PPP Fraction	(2) FinTech PPP Fraction	(3) FinTech PPP Fraction	(4) FinTech PPP Fraction
COVID Case Rate	0.81***			
	(0.24)			
Log Branches	−0.015***	−0.016***	−0.017***	−0.00033
	(0.0025)	(0.0027)	(0.0035)	(0.0070)
COVID Case Rate × Log Branches		−0.11***		
		(0.041)		
Unemp. Chg			0.016***	
			(0.0048)	
Unemp. Chg × Log Branches				−0.0053***
				(0.0017)
Observations	35,332	35,355	17,093	17,097
R^2	0.589	0.691	0.562	0.693
County FEs		X		X
CZ FEs	X		X	

This table presents regression results on the relationship between the share of FinTech PPP lending and ZIP code level statistics, interacted with the change in COVID-19 case rate in March 2020 per 100 people and the four-week change in unemployment as of April 11, 2020. Columns (1) and (3) use Commuting Zone fixed effects because the case rate and change in unemployment are observed at the county level. Columns with unemployment data have fewer observations because unemployment rates are not available for all counties. Estimates are weighted by PPP loans per ZIP code. Standard errors, corrected for clustering of observations at the county level, are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Data source: SBA PPP loan database and FDIC Summary of Deposits database.

that borrowers learned about FinTech lenders in particular. First, many borrowers, especially those who were denied loans by a traditional bank, searched for PPP loans online and came across FinTech lenders. Second, community banks without the capacity to make loans themselves may have referred borrowers to the FinTechs, in some cases without informing the FinTech lenders that they were doing this.

5.2. Banking relationships

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

[30] One prominent nonprofit was Our Fair Share, which was founded by musician Sean Combs to provide information about PPP and other government programs to minority entrepreneurs.

Table 6
FinTech lending and firm relationships.

	(1) FinTech PPP Loan	(2) FinTech PPP Loan	(3) FinTech PPP Loan	(4) FinTech PPP Loan	(5) FinTech PPP Loan
Log(PPP/SBA 7a)	0.030***				
	(0.011)				
Industry Emp. Growth		−0.33***			
		(0.084)			
One-Pers. Firm			0.11***		
			(0.0076)		
Log Jobs Supported				−0.048***	
				(0.0025)	
Log Approved Amt					−0.036***
					(0.0018)
Observations	4,768,973	3,954,530	4,979,333	4,979,117	4,979,316
R^2	0.124	0.133	0.201	0.205	0.199
Zip FEs	X	X	X	X	X
NAICS2 FEs	X	X			
NAICS6 FEs			X	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 2018–2019, measured at the NAICS 6-digit level. This variable is only available in ZIP codes where 7(a) loans occurred, so columns which include it have fewer observations. Industry emp. growth measures employment growth by 3-digit NAICS industry between the March and April Current Employment Statistics. One-Pers. firm is an indicator for sole proprietorships, S-Corps and individuals as indicated in the PPP data. Log approved amount is the log of the approved amount of the PPP loan. Standard errors double-clustered by NAICS 6-digit industry and ZIP code. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

of lenders. We know that banks create and maintain relationships with borrowers (see, e.g., seminal papers by Diamond, 1984; Petersen and Rajan, 1994), and these relationships are particularly important for the types of small and privately held firms that the PPP program targeted. We would ideally directly observe borrowers' relationship with banks, but in the absence of this data, we rely on proxies shown by previous research and to be associated with bank relationships. One such proxy is the number of bank branches in each ZIP code, since research has shown that bank relationships are highly localized. Next, we support this proxy using variation in borrowing relationship intensity by industry and borrower size among different types of borrowers that are located in the same ZIP code.

To measure exposure to the formal banking system, we measure pre-COVID banking system access at the industry level. Using the 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's traditional banks, firms in industries that 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 that demanded many PPP loans, but previously had few SBA 7(a) loans, are less likely 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 6. 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 non-banks. Based on the estimates in Column 1, firms in an industry with 10 percent more PPP loans than SBA loans would get 0.3 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 0.3 percentage points sounds small, it is economically meaningful given that only 10 percent of all PPP loans are from FinTechs. Note that we include controls for fixed effects at the NAICS 2-digit level to control for differences in demand by sector.

In the second column of Table 6, 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 harder-hit industries that were underserved by banks.

Another measure of exposure to traditional banking is presented in Column (3) of Table 6: an indicator for firms that applied for the PPP loans that are structured as a sole proprietorship, an S-Corp or as self-employed individuals.[31] These *one-person* firms, which are unlikely to have a formal borrowing relationship with a traditional bank, are more than 11 percentage points more likely to borrow from a FinTech PPP provider. As expected, this effect is very significant not only statistically but also economically.

The estimates in Column (3) showed that FinTech lenders provided more PPP loans to small borrowers. Part of the reason for this may have been that they were more willing to make very small loans. The last two columns of Table 6 directly consider the question of loan sizes. We estimate that FinTech PPP loans were about 4% smaller and

[31] S-Corps often have more than one employee, but they are often smaller than other corporate forms.

supported 5% fewer jobs. One way to interpret the former coefficient is to observe that the standard deviation of the log loan amount is about 1.5, so loans which are one standard deviation smaller are about 5 percentage points less likely to come from a FinTech lender. Considering that only 15% of loans come from FinTech lenders, this is an economically large effect. These estimates control for industry and ZIP code fixed effects, so they are not driven by borrowers that serve different industries or different regions, but rather by within-region or industry differences in the size of loans.

These results show that banks base their lending on past relationships and constrain themselves around their branches.[32] FinTech lenders do not have geographic constraints based on the presence of loan officers or physical bank branches. Despite this observation, 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 disproportionately 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.

5.3. Borrowing relationships with FinTechs

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 2018 to 2019 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 7 Columns (1) and (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.[33] 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 0.012 including controls. A one-standard deviation change in the 7(a) FinTech share is 13 percentage points, so ZIP codes with a one standard deviation higher FinTech 7(a) share have less than 0.2 percentage points more FinTech PPP loans. 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 7. 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. The coefficient in Column (4) is 0.8. One standard deviation of the desktop share is about 11 percentage points, which is therefore associated with 0.9 percentage points more FinTech loans. A possible reason for this change in the coefficient 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. Note that, in all specifications, the coefficient on log bank branches remains statistically and economically significant.

Another possible explanation for FinTech lending in areas underserved by banks is selective and increased advertising in these areas during the COVID-19 shock. From our discussions with FinTech lenders, we learned that FinTechs did not engage in particular marketing pushes during this time relative to traditional banks. But we would like to confirm this using the data. Using time-series data from Kantar Media, as provided by Adspender, we analyze commercial and business financial services advertising dollars by FinTech lenders and traditional Lenders through July, 2020. We hand-matched our bank and top-30 FinTech PPP lenders to create this sample and present monthly averages of advertisement dollars by quarter in the Appendix Fig. A.5. Excluding American Express and CapitalOne, which do primarily credit card advertising, we find

[32] In Phases 1 and 2 of the PPP program, there was a three-tier fee structure of payments to lenders, with lenders being compensated the least for loans with a value below $350,000. If the fees for small loans had been larger, would banks have made more of them relative to FinTechs? Overall, we do not think so: First, as shown in Table 4, banks' behavior was similar above and below this threshold in Phases 1 and 2. Second, the fee amount for small loans was increased in Phase 3, which led to even greater FinTech participation relative to bank participation.

[33] One caveat with this loan-level measure of past relationships is that it does not capture any other possible connection between these Fintech lenders and their PPP borrowers. One possibility, for example, is that these borrowers had some prior experience in payroll processing with these FinTech lenders (e.g., PayPal or Intuit). We have some anecdotal evidence on this type of relationship creating a lending relationship for some borrowers in the PPP program: https://www.businessinsider.com/how-small-businesses-can-access-ppp-loans-through-fintech-services-2020-4 as of March 2022.

Table 7
Local technology use and PPP lending.

	(1) FinTech PPP Fraction	(2) FinTech PPP Fraction	(3) FinTech PPP Fraction	(4) FinTech PPP Fraction
FinTech 7(a) Share	0.010	0.012**		
	(0.0067)	(0.0050)		
Fraction w Desktop			−0.22***	0.080***
			(0.013)	(0.018)
Log Med. Inc		−0.018***		−0.033***
		(0.0036)		(0.0040)
Frac Commute 45+m		0.15***		0.15***
		(0.015)		(0.013)
Frac White		−0.17***		−0.18***
		(0.0090)		(0.0087)
Log Branches		−0.020***		−0.020***
		(0.0013)		(0.0012)
Log Population		0.028***		0.026***
		(0.0014)		(0.0011)
Establishments Per Cap.		0.0011		−0.0015
		(0.0037)		(0.0040)
Frac Estabs <10 Emp		0.19***		0.17***
		(0.013)		(0.010)
Frac Estabs <500 Emp		−0.17***		−0.16***
		(0.027)		(0.010)
Observations	15,361	14,938	30,976	28,573
R^2	0.679	0.811	0.707	0.807
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 in the years 2018–2019. “Fraction w Desktop” is the fraction of households in the ZIP code with a desktop computer, as reported in the 2014–2018 ACS. See Appendix C for all variable definitions. Regressions are weighted by the total number of PPP loans per ZIP code. Robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Data sources: SBA 7(a) and PPP data, and US Census/ACS data.

a general decline in FinTech advertising dollars, which are mostly dedicated to national, cable-TV advertising, in 2020 with no change in this trend during COVID-19 period. If anything, we see an increase in spending on ads by traditional banks in the third quarter of 2020.

Overall, in this section, 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, computer access seems to be more important for the geography of FinTech PPP lending.

5.4. Demand for PPP and other aid programs

The PPP program was just one of many government programs intended to help small businesses hurt by the pandemic-led recession. Alongside the PPP program, other programs introduced by the Coronavirus Aid, Relief, and Economic Security (CARES) Act include expanded Economic Injury Disaster Loans (EIDL), greater unemployment benefits in the form of the Pandemic Unemployment Assistance (PUA) program, and a loan program known as the Main Street Lending Program (MSL). State and local governments instituted a variety of additional local programs.

Availability of other government programs could have affected the demand for the PPP program, and in particular, for the FinTech PPP loans. If this is the case, the demand for FinTech PPP loans and other programs would be correlated. To shed light on this question, we measure whether there was substantial overlap in the types of businesses that various programs served and the PPP loan provision specifically by FinTech lenders. This analysis can inform us about whether FinTech PPP demand would have been greater in the absence of other programs.

Ideally, we would use ZIP-code level data on the use of other government programs and estimate similar regressions as in the previous sections. To the best of our knowledge, granular local data on the use of most aid programs does not exist. Therefore, in Table 8, we use the Small Business Pulse Survey (SBPS) from the U.S. Census Bureau to compare cross-industry use of aid programs. The SBPS is a survey of small business performance, program use, and economic expectations administered on a weekly basis beginning in late April, 2020. The data for this survey is released on an aggregated basis for each week. We use a version of the survey compiled by NAICS 3-digit industry code.

The first two columns of Table 8 verify that the data actually capture useful variation by industry and are in line with our previous findings. Each observation is an industry-by-week pair, and all specifications have week fixed effects so that the identifying variation is within-week, cross-industry. Standard errors are clustered by industry. In Column (1), the dependent variable is the fraction of firms applying for the PPP program by industry, and the independent variable is a self-reported measure of economic performance during the COVID-19 crisis from the survey. The estimate shows that greater economic success during COVID is associated with less PPP demand, as we showed before. Confirming our previous results, Column (2) shows that a worse economic shock is associated with a higher fraction of PPP loans coming from FinTech lenders.

Table 8
Demand for assistance programs and FinTech PPP fraction.

	(1) Frac Applying for PPP	(2) FinTech PPP Frac	(3) FinTech PPP Frac	(4) FinTech PPP Frac	(5) FinTech PPP Frac	(6) FinTech PPP Frac	(7) FinTech PPP Frac
Success During COVID	−0.18***	−0.096**					
	(0.034)	(0.040)					
Pct Denied PPP			0.16***				
			(0.044)				
EIDL				0.085			
				(0.14)			
SBA Forgiveness					0.11		
					(0.20)		
Federal Assistance						−0.29	
						(0.22)	
State/Local Assistance							0.15
							(0.32)
Observations	863	863	860	863	863	863	863
R^2	0.361	0.833	0.851	0.847	0.847	0.847	0.847
Week FEs	X	X	X	X	X	X	X
Shock Ctrls			X	X	X	X	X

This table shows how demand for various government programs is related to FinTech use. Each observation is a week-by-3 digit NAICS industry pair. Column 1 shows the relationship between the fraction of survey respondents reporting PPP applications and the average magnitude of the economic shock due to COVID as reported by survey respondents (with positive numbers indicating greater success). In Columns 2–5, the dependent variable is fraction of PPP loans from FinTech lenders. The independent variable in Column 3 is the fraction of respondents reporting PPP loan denial. The independent variables in Columns 4–7 are the fraction of respondents requesting assistance from various programs. Respectively, they are Economic Injury and Disaster Loans, SBA Loan Forgiveness, other non-unemployment Federal Assistance, and state/local government assistance. All columns control for week fixed effects and are weighted by the number of PPP loans originated for that industry-week combination. Columns 3–7 also control for a fraction of respondents reporting economic shocks of each possible magnitude. Standard errors, corrected for clustering of observations at the 3-digit NAICS industry level, are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Data sources: SBA PPP database and U.S. Census Bureau Small Business Pulse Survey.

Next, we study the relationship between the use of PPP loans and other programs. Our dependent variable is the fraction of PPP loans coming from FinTech lenders in that week and industry. The independent variable in Column (3) is the fraction of borrowers who did not receive PPP loans despite applying. We control for economic performance using the self-reported success measure considered in Columns 1–2. Note that it is not necessarily the same borrowers getting denied and (ultimately) getting their loans from FinTechs, as our analyses are at the industry level. Rather, this finding likely reflects the fact that, in some industries, borrowers had a harder time accessing the traditional banking system, and, in those same industries, borrowers had more success with FinTechs.

Columns (4), (5), (6) and (7) of Table 8 consider the substitution patterns between FinTech PPP loans and other forms of government assistance. We study the four types of programs with well-populated data in the Census Bureau's SBPS: Economic Injury and Disaster Loans (EIDL), SBA Loan Forgiveness, other forms of federal assistance, and state/local assistance. Our question here is not whether PPP and other government programs are substitutes in general, but rather whether access to other programs affects demand specifically for FinTech PPP. The dependent variable is again the fraction of PPP loans originated by FinTech lenders at the industry level; and, we use the fraction of borrowers applying to each program as our independent variable.

We do not find a strong relationship between FinTech PPP program provision and the use of other programs — in none of the specifications is the relationship large or statistically significant. We think it is likely that other government programs affect demand for PPP in general. But insofar this occurs, it causes substitution to both FinTech PPP lenders and to traditional banks.

6. How substitutable are FinTech loans?

An important question is whether FinTechs expand the overall loan supply by providing PPP loans to new types of borrowers who otherwise would not have gotten PPP loans, or whether their presence just leads to substitution away from banks. We have shown that borrowers in regions with fewer branches or with weaker ties to the banking system are more likely to borrow from FinTech lenders. But this finding does not necessarily imply that FinTechs lend to a new segment of borrowers. If borrowers with weak ties to the banking system find FinTech lending more convenient, then it is possible that they get PPP loans from FinTechs that they would have gotten from banks if FinTech loans had not been available. On the other hand, if FinTechs expand access into an altogether new market, then we would expect little substitution between FinTech lenders and banks.

To shed light on this question, we study whether borrowers substitute to FinTech lenders in traditional banking regions, where traditional banks' PPP loan supply is constrained. If the FinTech and traditional bank markets are relatively segmented, then we would not expect much substitution between FinTech and traditional bank PPP loans in these regions with bank branches.

6.1. Shift share design

Our identification strategy relies on differences in traditional banks' overall 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 at the national level and create a measure of predicted bank responsiveness that will allow us to estimate whether a lower loan supply from traditional banks causes substitution to FinTech lenders instead. The advantage of measuring predicted responsiveness, rather than realized responsiveness, is that the realized PPP loan supply from banks in any particular region may be a function of the demand factors that could also affect FinTech demand. For example, if borrowers in a region do not have good internet access, they might demand few FinTech PPP loans and more traditional bank PPP loans instead. By predicting banks' responsiveness based on their national lending patterns, we hope to create a measure of traditional bank PPP loan supply that is independent of such demand-side shocks to PPP loan demand.

We create our predicted-PPP measure in two steps, following the literature on shift-share (or "Bartik") designs. First, we measure log PPP loans per bank branch (the log of PPP loans divided by the number of bank branches) at the bank level. We limit the sample to banks with assets of above $1bn, to remove small community banks from the sample. We calculate this measure separately for each bank and each state, taking the average using only bank branches and loans in *other* states. This is our measure of bank "responsiveness" to the PPP program, denoted as g_{bl} for branches in ZIP code l belonging to bank b.

In the second step, we calculate the average responsiveness by ZIP code of banks located there as

$$x_l = \sum g_{bl} z_{bl},$$

where z_{bl} is the fraction of branches in ZIP code l belonging to bank b. If all banks in ZIP code l did exactly as much PPP lending per branch as they did on average in other states, then x_l would perfectly predict the number of PPP loans that were originated by those banks. Perfect prediction is highly unlikely, though, and it is not necessary.

Goldsmith-Pinkham et al. (2020) outline a set of assumptions under which shift-share designs identify meaningful causal effects. Following their paper, our identifying assumption is that the average origination volume of traditional banks (calculated on a national basis) is unrelated to PPP demand where their branches are located. Measuring the average rate of PPP origination using branches located in other states, as we do, purges the predicted PPP measure of state-level COVID-19 restrictions or any other local conditions, which might affect both FinTech demand and traditional bank loan supply.

We further build on the suggestions in Goldsmith-Pinkham et al. (2020) to support our identifying assumption. An important way of supporting the design is with is a "pre-trends" test, in which lagged values of the independent variable are regressed on the instrument. The ideal pre-trends test would use data on an older version of the PPP program. Since the PPP program begins only following the COVID crisis, we use the next-best substitute and measure FinTech participation in the SBA's 7(a) program. Column (1) of Table 9 shows estimates from specification where the independent variable is the shift-share instrument and the dependent variable is the FinTech share of 7(a) loans.

Following another proposal by Goldsmith-Pinkham et al. (2020), we also show that our measure is unrelated to a large number of variables that we might think to be related to FinTech demand. In the previous sections, we showed that FinTech demand could be affected by the types of firms in an area, the persistence of relationships, local technology use, and several other factors. Therefore, we would like to show here that our loan supply measure is uncorrelated to these variables. In the remaining columns of Table 9, we regress measures of each of these factors on our measure of FinTech demand. Out of 10 variables, only one of them is statistically significant at the 10% level.

We are also interested in understanding which particular banks are most important in our shift-share design. Goldsmith-Pinkham et al. (2020) derive "Rotemberg weights" which, intuitively, measure the relative importance of the shifters for the overall instrumental variables estimate. In our setting, banks with high Rotemberg weights are the ones that originated many PPP loans, and are disproportionately important in areas with a high FinTech share. One reason to look at these weights is that it might be concerning if a small number of banks with some unusual characteristics are driving the overall analysis.[34] The banks with the largest and smallest Rotemberg weights are shown in Appendix B.4. Table A.8 tests the possible hypothesis that banks with larger Rotemberg weights are special in some way. The results in that table show that there does not appear to be a detectable relationship between bank characteristic (log assets, deposits over assets, loans over assets, interest income over loans, and C&I loans over loans)and weights.

6.2. Shift share substitution results

Table 10 shows the effect of predicted PPP bank lending on lending by traditional banks and by FinTech lenders. Panel A shows the effects by bank type and by date. In Column (1), we present the relationship between log predicted PPP loans by traditional banks and log realized PPP loans by traditional banks. As in the other tables, we control for log establishments and include county fixed effects. The estimated coefficient on log predicted PPP loans is 0.03 and significant at the 1% level, indicating that predicted lending is associated with actual lending, but much less than one-for-one.[35] Columns (2) and (3) show the effect

[34] The Rotemberg weights are guaranteed to sum to 1, but are not bounded between 0 and 1. Banks can have negative Rotemberg weights if they do a lot of PPP lending and have branches located in areas with few traditional bank PPP loans, for example.

[35] The main reason the effect is substantially less than one-for-one is that predicted PPP lending based on other states only predicts a particular branch's lending to a limited degree. Another reason is that the estimates control for county fixed effects, so the estimates are identified by differences in predicted lending across ZIP codes within the same county. Since borrowers do not limit themselves to choosing a bank in their ZIP code of residence and may substitute from one traditional bank to another within the same county, the coefficient is smaller than if they stayed only in one ZIP code.

Table 9
Predicted bank lending and local covariates.

	(1) Frac 7(a) FinTech	(2) PUA Claims (CA only)	(3) UI Claims (CA only)	(4) Bank Branches	(5) Population	(6) Pop Fraction White	(7) Frac With Desktop	(8) Frac With Internet	(9) Frac Estabs <10 Emp	(10) Frac Estabs <500 Emp
Predicted PPP	0.0055	−0.036	0.0038	0.018	−0.020	0.010	0.0078*	0.0049	0.00081	0.00027
	(0.0051)	(0.056)	(0.035)	(0.034)	(0.027)	(0.0069)	(0.0040)	(0.0037)	(0.0026)	(0.00020)
Observations	10,807	994	1004	13,164	12,894	12,914	12,805	12,805	13,044	13,044
R^2	0.316	0.341	0.272	0.203	0.379	0.480	0.430	0.454	0.368	0.197
County FEs	X	X	X	X	X	X	X	X	X	X

ZIP code level specifications showing the relationship between the predicted number of bank PPP loans and predetermined covariates. Data calculated from the FDIC Summary of Deposits database, SBA PPP loan data, the American Community Survey, and Chetty et al. (2020). Pandemic Unemployment Assistance (PUA) and Unemployment Insurance (UI) claims are available only for ZIP codes in Califronia. PUA Claims, UI Claims, bank branches, population and SBA loans are measured in logs. The independent variable *Predicted PPP* is constructed using a shift-share methodology as described in Section 6. Sample only includes ZIP codes with bank branches. Estimates are weighted by PPP loans per ZIP code. Robust standard errors.

Table 10
Effects of predicted bank lending.

	A. Effect of predicted lending on traditional and FinTech lending, by date					
	(1) Traditional PPP	(2) Traditional PPP Before May 4	(3) Traditional PPP After May 5	(4) FinTech PPP	(5) FinTech PPP Before May 4	(6) FinTech PPP After May 5
Predicted PPP	0.028***	0.029***	0.014	−0.042**	−0.011	−0.049**
	(0.0069)	(0.0077)	(0.011)	(0.017)	(0.015)	(0.021)
Log Establishments	0.97***	1.01***	0.83***	0.81***	0.95***	0.73***
	(0.0032)	(0.0035)	(0.0051)	(0.0089)	(0.0071)	(0.011)
Observations	12,101	12,092	11,804	12,166	11,494	11,656
R^2	0.932	0.925	0.796	0.917	0.919	0.885
County FEs	X	X	X	X	X	X
	B. Effect of predicted lending on FinTech lending, by borrower type					
	(1) Above Median Branches	(2) Below Median Branches	(3) Below $10,000	(4) Above $10,000	(5) Solo Borrower	(6) Large Borrower
Predicted PPP	−0.064	−0.053***	−0.023	−0.050***	−0.046***	−0.038**
	(0.039)	(0.018)	(0.019)	(0.017)	(0.017)	(0.016)
Log Establishments	0.80***	0.95***	0.73***	0.90***	0.84***	0.89***
	(0.020)	(0.010)	(0.0084)	(0.0070)	(0.0077)	(0.0070)
Observations	3076	7565	9857	11,005	10,720	10,646
R^2	0.497	0.665	0.483	0.723	0.633	0.715
County FEs	X	X	X	X	X	X

This table presents ZIP-code level specifications showing the relationship between the predicted log number of traditional bank PPP loans, and the log number of PPP loans from traditional banks and from FinTech lenders. Sample includes only ZIP codes with bank branches. In Panel A, Column 1 shows the effect of predicted lending on log total PPP lending from traditional banks. Columns 2–3 show the same result as Column 1, but split before and after May 4. Column 4 shows the effect of predicted traditional bank lending on FinTech PPP lending, and Columns 5–6 split this before and after May 4. In Panel B, all results are for FinTech PPP loans. Columns (1) and (2) are limited to ZIP codes with above and below the median number of bank branches respectively. Columns (3) and (4) show results for loans above and below an amount of $10,000. Column (5) shows results for S-Corps, Sole Proprieterships and Self-Employed Individuals, and Column (6) shows results for all other borrower types. All estimates are weighted by PPP loans per ZIP code. Robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Data sources: SBA PPP loan and FDIC Summary of Deposits databases.

of predicted PPP lending on realized PPP lending by date. Our predictions affect actual PPP lending mostly in the first weeks of the program, when supply constraints by traditional banks were most severe.[36]

Columns (4)-(6) show how predicted lending by banks is associated with realized PPP loans from FinTech lenders. The negative and statistically significant coefficient in Column (4) means that there is a statistically significant degree of substitution between traditional bank PPP lending and FinTech PPP lending.[37]

While the results in this table are statistically significant, the degree of substitution between FinTechs and traditional banks is much lower than one-for-one. Interpreting the regression coefficients, an additional 15 traditional bank PPP loans in the average ZIP code results in about 4 fewer PPP loans from FinTech lenders, implying a substitution of around 27%.[38] Columns (5) and (6) show the effects

[36] We split the data based on the drop-off that occurs after May 5, which is visible in Fig. 1.

[37] To supplement the reduced-form estimates shown in Table 10, Table A.6 shows instrumental variables estimates. The estimates show results from an IV specification in which predicted PPP lending is an instrument for lending by traditional banks and lending by FinTechs is the dependent variable. The estimates from that table confirm our reduced form results.

[38] The coefficient on traditional banks is 0.028, which corresponds to about 15 PPP loans given an average of 620 PPP loans per ZIP code, 85% of which are from traditional banks. The coefficient on FinTech PPP is about 0.042, which corresponds to about 4 loans.

on FinTech lending split by date. The effects on FinTech lending are statistically significant only in the later weeks of the program, which is a potential sign that substitution from traditional banks to FinTechs took several weeks as borrowers spent time finding a new lender. The fact that the results occur with a lag suggests that it takes time for small business owners to reapply to a FinTech lender after being denied by a bank.

This finding indicates that substitution from traditional banks to FinTech lenders replaces only about one-quarter of the traditional bank PPP loans that are not made because banks were not responsive to the program. This provides evidence that the FinTech and traditional bank lending markets are relatively segmented; and FinTech lenders supply services to a new and relatively distinct market than traditional banks. An important note, however, is that these estimates come from ZIP codes where bank branches are located, and they are weighted by the number of branches per ZIP code. Substitution may be larger in ZIP codes where fewer branches operate –i.e., the ZIP codes where FinTech loans are more common.

We explore the degree of substitution for different subgroups of borrowers and ZIP codes in Panel B of Table 10. We split ZIP codes and borrowers based on the classifications developed in the previous sections: By number of branches per ZIP code (Columns (1) and (2)), by loan amount (Columns (3) and (4)) and by firm type (Columns (5) and (6)). We do not find large differences in the degree of substitution in more-or-less banked ZIP codes. However, the degree of substitution is economically smaller for very small loans — below $10,000. The lack of substitution for small loans provides evidence that it is for precisely these types of loans that markets are the most segmented.

7. Possible costs of FinTech participation

Our paper provides strong evidence that FinTech lenders expanded the pie of access to PPP loans, especially in areas underserved by banks and in lower-income areas with a larger share of the minority population. However, one should acknowledge that there could be costs of FinTech involvement in government programs like the PPP.

These potential costs include (but are not limited to) fraud, being easier in an online application for credit and by borrowers with no prior relationship with traditional banks. There is, in fact, a recent paper by Griffin et al. (2021) who show that FinTech lenders were significantly more associated with fraudulent reporting by borrowers to get PPP loans. They use four metrics to detect this potential misreporting: non-registered businesses, multiple businesses in the same residential address, abnormally high implied compensation per employee of the borrowing firms, and inconsistencies with jobs reported for another government aid program – EIDL – that ran at similar times. The authors identify Capital Plus, Prestamos CDFI, MBE, and Harvest as FinTech lenders in the top 10 for all four flags; and additionally Itria, Fountainhead, Benworth as FinTech lenders in the top 10 for at least three of four flags. In Appendix Table A.7, we show that our main results remain unchanged when we exclude these FinTech lenders from our sample (see Columns 1 and 2). Note that the coefficients on the log bank branches or other variables remain both statistically significant and economically unchanged, excluding FinTech lenders possibly associated with fraudulent borrower reporting.

In Column 3, we test for robustness of our results to excluding one-person firms (independent contractors, self-employed, or sole-proprietorships), as two of the four flags used in Griffin et al. (2021) – i.e., multiple loans to the same borrower address and jobs reported to EIDL exceeding jobs reported to the PPP– apply mostly to individual borrowers. Note that we take an extremely conservative approach and exclude all one-person firms rather than borrowers of the flagged lenders only. Therefore, in Column 3, the economic significance of the coefficient on our main explanatory variable, log bank branches, falls as Fintech lenders overall were important lenders to one-person firms. Nevertheless, the coefficient remains statistically significant, and our main finding remains robust.[39]

Other potential costs due to FinTech lenders' participation in such government programs could involve possible privacy issues and predatory lending. PPP applications include confidential information on individuals and private firms, and the governments have to rely on unregulated FinTech institutions to protect this confidential information about borrowers and not use it for predatory lending in the future. These issues could be more of a concern in underserved areas.

Liquidity or concentration risk is another potential cost as many of these FinTech lenders partnered with a handful of online banks, which ended up making large number of PPP loans per branch. Typical examples are Cross River Bank, which extended almost 200,000 loans, and Celtic Bank, which extended almost 150,000 loans, with only one branch each. Such potential costs of FinTech involvement in government programs are fruitful topics for future research.

8. Conclusion

This paper studies whether FinTech lenders provide access to financial services in regions and by industries that are not served by the traditional banking system. When we compare different regions of the country, 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, however, FinTech lenders disproportionately serve industries and ZIP codes with less access to traditional finance.

ZIP codes with fewer bank branches, lower median income, and a larger fraction of the minority population get more of their PPP loans from these types of new lenders. Across industries, firms in industry codes that previously got fewer SBA loans were more likely to get their PPP loans from FinTech lenders. Finally, we show that in ZIP codes where traditional banks keep branches but end up not participating in PPP origination, only a small fraction of local small businesses turned to FinTech online banks and non-

[39] In unreported tests, we also show the robustness of our main findings to excluding Kabbage, which is the largest nonbank lender, or Cross River Bank, which is the largest online lender, from our sample.

banks instead. The substitution, however, is likely to be substantially larger in ZIP codes that are underserved by the traditional banking system.

This paper systematically studies the first government program where traditional banks and FinTech lenders can be compared in terms of their responsiveness to the demand by small businesses for exactly the same type of financial service. Therefore, it has important policy implications, which speak to allowing (more) FinTech lenders to participate in any type of fully or partially-guaranteed government loan program (e.g., SBA 7a loans) in a timely manner to increase the efficiency of small-business lending not only during crises but also in non-crisis periods. We also discuss potential costs of involving FinTech lenders in government's liquidity injection programs like the PPP, where applications are made online and loans are processed quickly. One of these potential costs is that fraudulent reporting by borrowers is more likely in FinTech lending with no prior relationship banking, as shown by Griffin et al. (2021). We show the robustness of our findings to excluding FinTechs flagged by this paper as the top lenders with possibly fraudulent PPP loans. We leave the overall welfare analysis of including FinTech lenders in such government programs, and the study of how to modify the program to alleviate fraud concerns, to future research.

Understanding exact mechanisms, whereby FinTech companies are able to provide services to borrowers underserved by the traditional banking system, in addition to possible costs, is a valuable topic for future research. Moreover, in this paper, we have focused on 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 also a fruitful area for future research.

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Appendix A

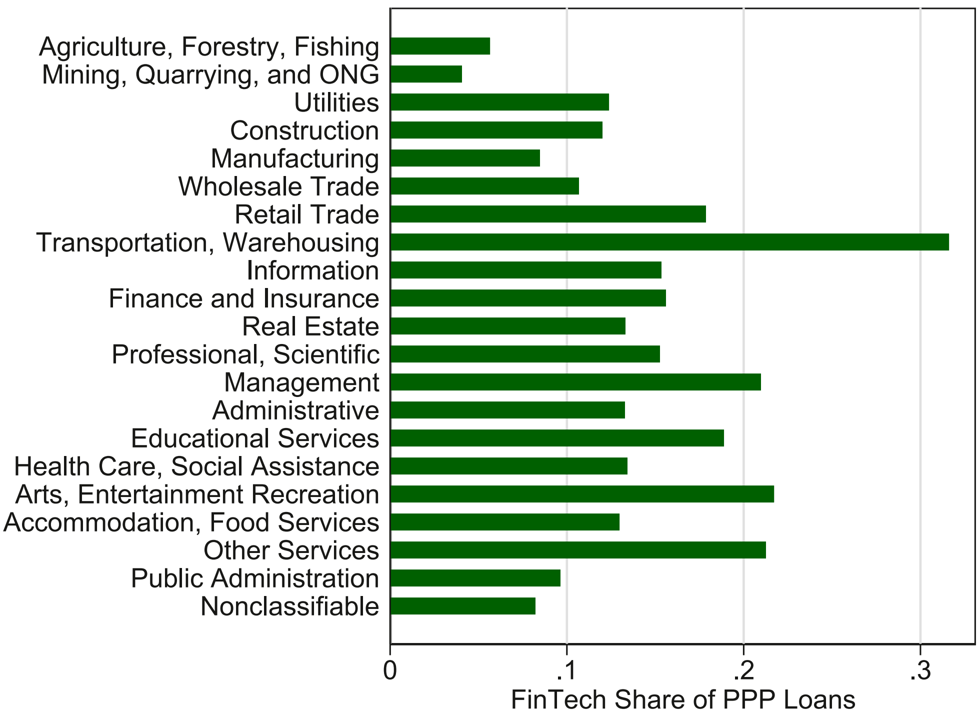

Fig. A.1. This graph presents the fraction of PPP loans originated by FinTech lenders, by borrowers' 2-digit NAICS industry classification. Data source: PPP Loan database.

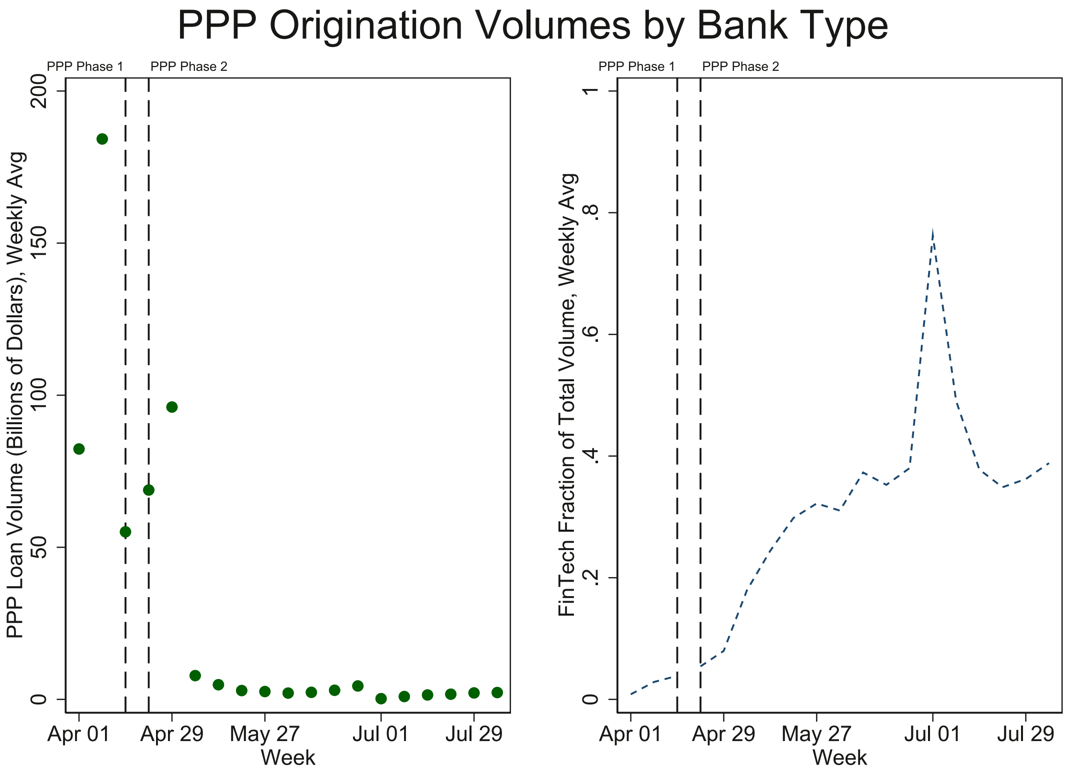

Fig. A.2. The figure shows the volume of PPP loans by approval week between April 3 and August 8, 2020. There is a gap between April 16, when PPP Phase 1 ended, and April 27, when Phase 2 began. Data source: SBA PPP Loan Database.

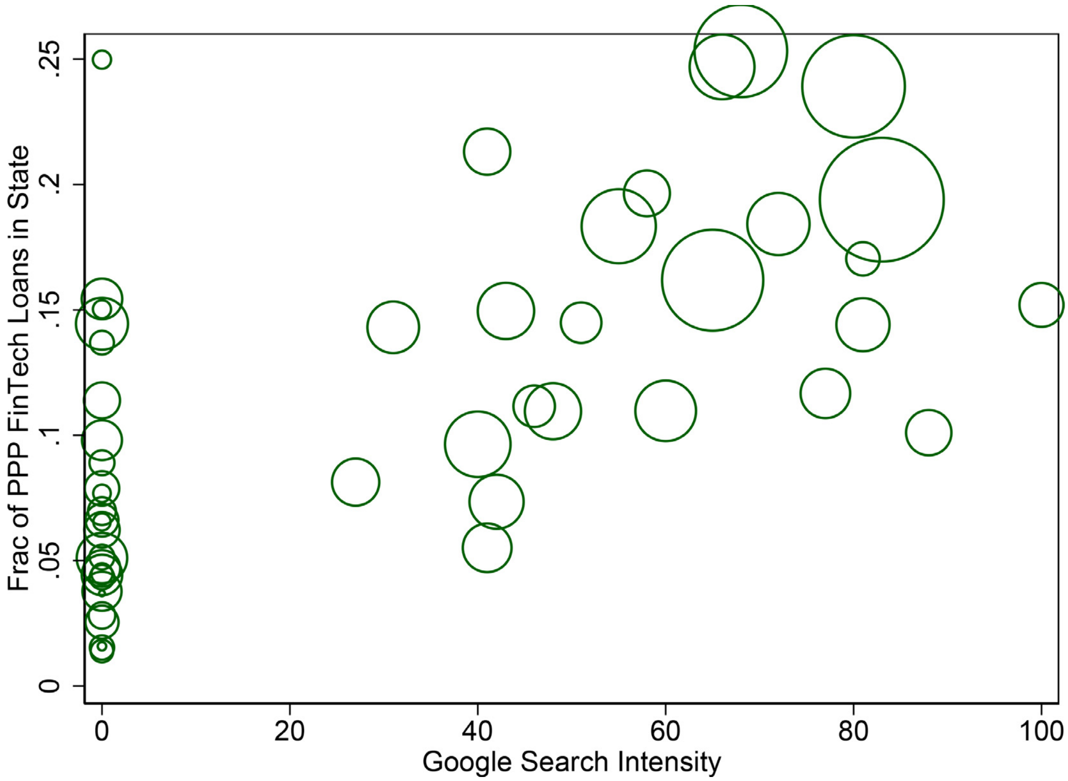

Fig. A.3. This figure shows the relationship between Google searches for online PPP loans and our measure of actual PPP loans, with missing states located at zero. Searches are for "apply ppp loan online" from 3/1/20 to 8/8/20. Each circle represents a state, weighted by the total number of PPP loans in each state.

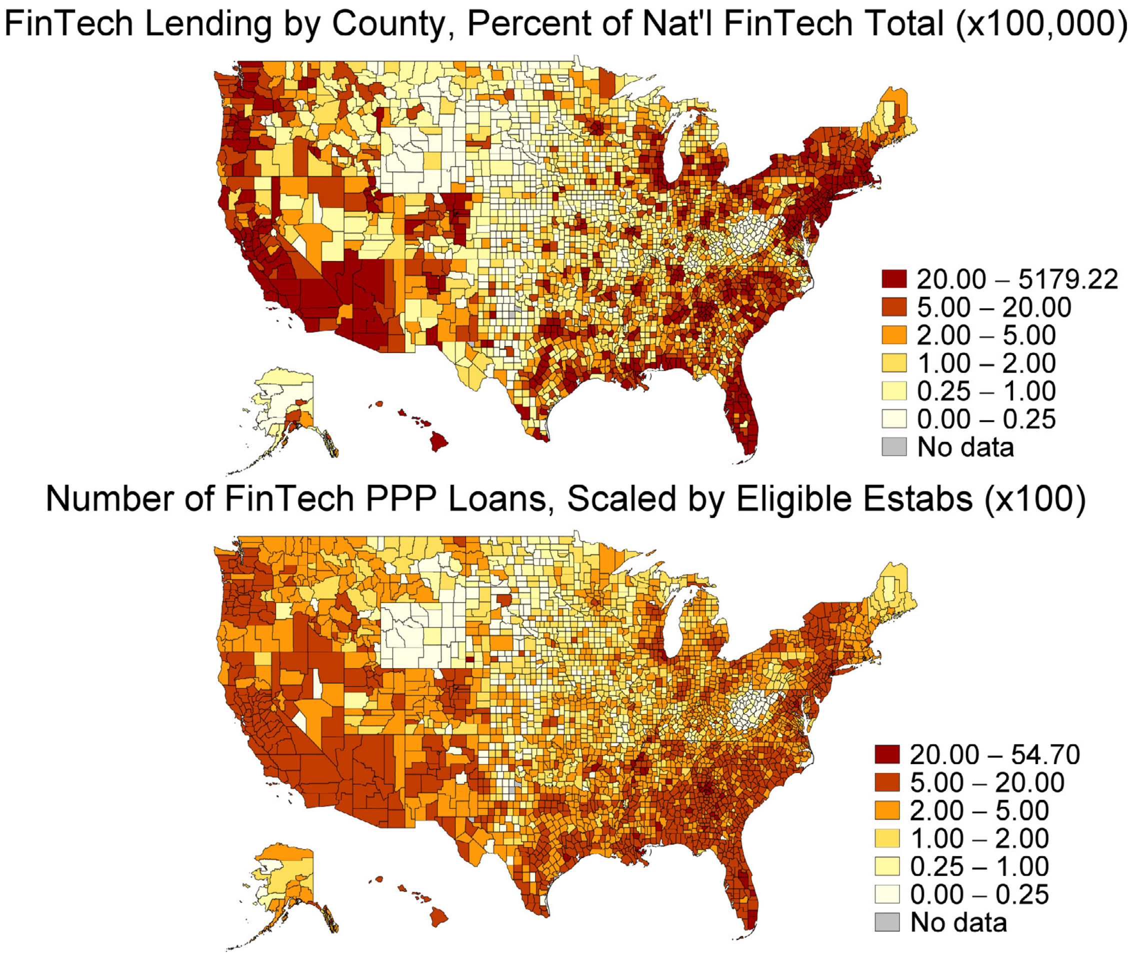

Fig. A.4. This figure shows the country-level graphs of FinTech PPP lending across U.S. Counties. Source: SBA PPP database. In the upper panel, we present the number of FinTech PPP loans by county, scaled by total FinTech loans nationally. In the lower panel, we scale the number of FinTech PPP loans by the total number of eligible establishments.

Table A.1
PPP lending by phase and lender type.

	Traditional bank	Non-bank	Online	Total
A. Number of PPP loans by phase and lender type				
Phase 1	1,538,844	42,929	25,625	1,607,398
Phase 2	2,800,183	279,018	427,770	3,506,971
Phase 3	1,375,917	2,156,021	222,911	3,754,849
Second Draw	2,055,637	702,333	143,179	2,901,149
Total	7,770,581	3,180,301	819,485	11,770,367
B. Loan volume by phase and lender type (1000s of dollars)				
Phase 1	313,624,712	4,696,578	3,398,168	321,719,458
Phase 2	180,339,543	9,250,127	14,118,654	203,708,324
Phase 3	29,463,586	35,256,597	4,342,318	69,062,501
Second Draw	186,492,134	16,704,701	5,254,991	208,451,826
Total	709,919,975	65,908,003	27,114,131	802,942,109

Traditional bank, non-bank and online bank PPP origination by phase. “Phase 3” excludes Second Draw PPP loans originated in Phase 3 of the program. Loan volume is measured in thousands of dollars.

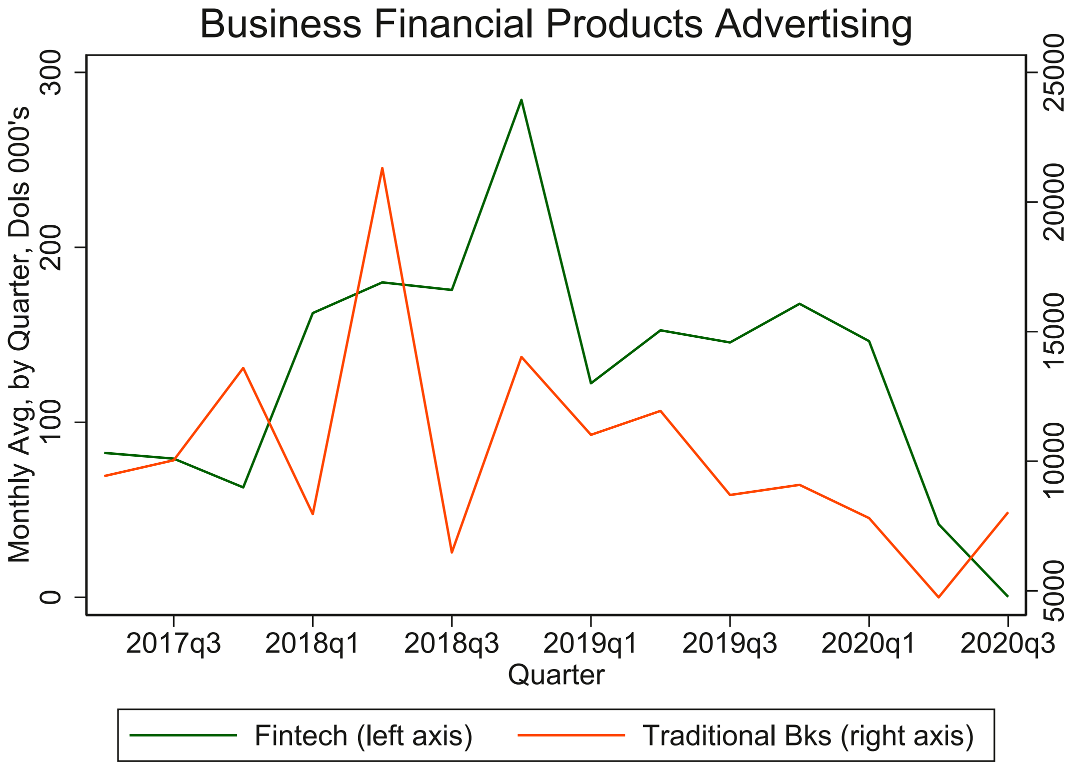

Fig. A.5. Commercial and Business Financial Services Advertising Dollars by FinTech and Non-Fintech Lenders. "FinTech" includes the top-30 FinTech PPP lenders excluding American Express and CapitalOne. Monthly averages by quarter through July, 2020. Data Source: Kantar Media.

Table A.2
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	−0.0076***	−0.0096***	−0.0095***	−0.010***
	(0.00058)	(0.00044)	(0.00074)	(0.00058)
Log Med. Inc			−0.011***	−0.0065***
			(0.0021)	(0.0015)
Frac Commute 45+m			0.077***	0.066***
			(0.0087)	(0.0060)
Frac White			−0.088***	−0.084***
			(0.0055)	(0.0037)
Log Population			0.015***	0.011***
			(0.00069)	(0.00055)
Establishments Per Cap.			−0.0023	0.0021
			(0.0021)	(0.0020)
Frac Estabs <10 Emp			0.096***	0.077***
			(0.0068)	(0.0051)
Frac Estabs <500 Emp			−0.089***	−0.075***
			(0.0065)	(0.0051)
Observations	35,543	35,543	28,577	28,577
R^2	0.691	0.630	0.783	0.741
County FEs	X	X	X	X

This table presents ZIP-code level specifications showing the relationship between the share of online and nonbank PPP lending, presented separately, and ZIP code level statistics, including the log number of bank branches. Estimates are weighted by PPP loans per ZIP code. Robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Data sources: Chetty et al. (2020), 2014–2018 American Community Survey and SBA PPP loan database.

Table A.3
Summary statistics by ZIP code (unweighted).

	Mean	Std. Dev	Median	Count
Frac Nonbank	0.05	0.09	0.01	36,267
Frac Online Bk	0.05	0.10	0.02	36,267
Total FinTech PPP Fraction	0.10	0.14	0.05	36,267
Frac Bk/CU	0.90	0.14	0.95	36,267
Num. PPP Lns	141.02	259.98	26.00	36,267
Median Income	59,586.32	25,260.42	54,375.00	29,736
Frac. 45 m + Commute	0.17	0.12	0.15	30,857
Frac. White	0.83	0.20	0.92	31,160
Population	4,605.77	6,763.84	1,343.00	31,223
Num. Bk Branches	4.54	4.90	3.00	19,369
COVID Case Rate	0.01	0.02	0.00	35,355
Unemp. Growth	2.95	1.79	2.63	17,097
Num. Estabs	235.36	410.04	46.00	33,571

This table presents unweighted summary statistics at the ZIP-code level. See Appendix C for variable definitions. Bank branches are for ZIP codes that have at least one branch. Unemployment data is not available for all regions. Data sources: SBA PPP database, FDIC Summary of Deposits database, Decennial Census/ACS, County Business Patterns.

Table A.4
FinTech share, key subsamples.

	FinTech share in select subsamples	
	FinTech share	Number of PPP loans
Hardest-Hit ZIP Codes	0.22	540,811
Hard-Hit Industries	0.22	1,173,913
Small Loans	0.24	1,022,936
Small Firms	0.24	1,704,158

FinTech share of loans in key subsamples. “Hardest-Hit ZIP Codes” are ZIP codes in the top population-weighted quintile of unemployment rate growth, March 14-April 11. “Hard-Hit Industries” are loans to industries in the bottom quintile (employment-weighted) of employment change from the March to the April 2020 CES, calculated by 3-digit NAICS code. “Small Loans” are in the smallest quintile of loans by initial approved amount. “Small Firms” are sole proprietorships, S-Corps and Self-Employed Individuals.

Table A.5
Number of branches in the ZIP code and FinTech PPP lending shares, by program phase.

	(1) FinTech PPP Fraction Phase 1	(2) FinTech PPP Fraction Phase 2	(3) FinTech PPP Fraction Phase 3	(4) FinTech PPP Fraction Second Draw
Log Branches	−0.0037***	−0.021***	−0.023***	−0.053***
	(0.00037)	(0.00062)	(0.00091)	(0.00094)
Log Med. Inc	0.0026***	−0.027***	−0.085***	−0.068***
	(0.00092)	(0.0015)	(0.0022)	(0.0022)
Frac Commute 45+m	0.039***	0.13***	0.0053	0.31***
	(0.0042)	(0.0063)	(0.0091)	(0.0096)
Frac White	−0.0063***	−0.19***	−0.22***	−0.35***
	(0.0021)	(0.0030)	(0.0039)	(0.0044)
Log Population	0.0072***	0.027***	0.053***	0.062***
	(0.00039)	(0.00068)	(0.0010)	(0.0010)
Establishments Per Cap.	−0.00074	−0.0014	−0.068***	−0.0085***
	(0.00086)	(0.0017)	(0.0054)	(0.0027)
Frac Estabs <10 Emp	0.054***	0.13***	−0.14***	0.19***
	(0.0036)	(0.0062)	(0.0083)	(0.0092)
Frac Estabs <500 Emp	−0.050***	−0.12***	0.018	−0.26***
	(0.0063)	(0.012)	(0.012)	(0.016)
Observations	27,007	27,920	27,425	27,516
R^2	0.683	0.783	0.933	0.836
County FEs	X	X	X	X

We present ZIP-code level specifications from linear regressions showing the relationship between the share of FinTech PPP lending and the number of bank branches per ZIP code. Estimates are as in Column 3 of Table 3, but with expanded data that includes PPP loans originated until May 2021. Estimates are weighted by PPP loans per ZIP code. Robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Data sources: Chetty et al. (2020) and SBA PPP loan database.

Table A.6
Effect of traditional bank PPP lending on FinTech PPP lending: instrumental variables estimates.

	(1) FinTech PPP	(2) FinTech PPP/ Before May 4	(3) FinTech PPP After May 5
Log PPP (Trad Bk)	−1.50**	−0.40	−1.75**
	(0.72)	(0.56)	(0.84)
Log Establishments	2.26***	1.34**	2.43***
	(0.70)	(0.54)	(0.82)
Observations	11,216	10,543	10,732
R^2	0.433	0.697	0.271
County FEs	X	X	X

Instrumental variable specifications showing the relationship between FinTech PPP lending and traditional bank PPP lending at the ZIP code level. Estimates are calculated using two-staged least squares specifications in which a shift-share variable is used as an instrument. The instrumented endogenous variable is the log number of traditional bank PPP loans. The dependent variable is the log total number of FinTech PPP loans (in Column 1), the log number of FinTech PPP loans with application date on or before May 4, (Column 2) and the log number of FinTech PPP loans with application date after May 4, (Column 3). Data calculated from ZIP business patterns and SBA PPP loan data. Robust standard errors. Estimates are weighted by establishments per ZIP code.

Table A.7
Loan-level estimates excluding high-fraud-potential loans.

	(1) FinTech Frac Low-Fraud Originators	(2) FinTech Frac Low-Fraud Originators (Alt Sample)	(3) FinTech Frac No Individuals
Log Branches	−0.019***	−0.019***	−0.0068***
	(0.0011)	(0.0011)	(0.00057)
Log Med. Inc	−0.017***	−0.017***	−0.0081***
	(0.0030)	(0.0030)	(0.0019)
Frac Commute 45+m	0.14***	0.14***	0.048***
	(0.012)	(0.012)	(0.0076)
Frac White	−0.17***	−0.17***	−0.061***
	(0.0077)	(0.0077)	(0.0041)
Log Population	0.026***	0.026***	0.012***
	(0.0010)	(0.0010)	(0.00054)
Establishments Per Cap.	−0.000082	−0.000085	0.0019**
	(0.0034)	(0.0033)	(0.00086)
Frac Estabs <10 Emp	0.17***	0.17***	0.11***
	(0.0097)	(0.0097)	(0.0056)
Frac Estabs <500 Emp	−0.16***	−0.16***	−0.096***
	(0.0092)	(0.0092)	(0.0061)
Observations	4,988,080	4,994,444	3,894,560
R^2	0.071	0.071	0.042
County FEs	X	X	X

Loan level specifications showing the relationship between the share of FinTech PPP lending and the number of bank branches per ZIP code. Standard errors clustered by ZIP code. Column 1 excludes PPP originators flagged as being among the top-10 in three or more of the indicators for fraud potential as determined by Griffin et al. (2021). Column 2 excludes PPP originators flagged as being among the top-10 in four of the indicators for fraud potential as determined by Griffin et al. (2021). Column 3 excludes all individual borrowers (independent contractors, self-employed, or sole-proprietorships).

Table A.8
Rotemberg weights and bank observables.

	(1) Rotemberg Weight	(2) Rotemberg Weight	(3) Rotemberg Weight	(4) Rotemberg Weight	(5) Rotemberg Weight	(6) Rotemberg Weight
Log(Assets)	−0.022					
	(0.019)					
Deposits/Assets		−0.073				
		(0.077)				
Loans/Assets			0.25			
			(0.21)			
Interest Inc/Loans				−3.12		
				(4.16)		
C&I Lns/Total Lns					−0.032	
					(0.038)	
Log(Num Branches)						−0.024
						(0.019)
Observations	294	294	294	294	255	294
R^2	0.047	0.001	0.025	0.002	0.003	0.044

Bank level specifications showing the relationship between Rotemberg weights and bank observables. Estimates from bivariate specifications in which the dependent variable is each bank's Rotemberg Weight and the independent variable is a bank-level variable (log assets, deposits over assets, loans over assets, interest income over loans, C&I loans over loans, and log number of branches). Data source: March 2020 call reports (FFIEC).

Appendix B. Lender classifications

B1. Non-bank lenders (600+ loans)

Non-depository financial institutions.

Lender	PPP Loans
Kabbage, Inc.	160,897
Readycap Lending, LLC	34,149
Intuit Financing Inc.	18,467
MBE Capital Partners	16,394
Fundbox, Inc.	13,543
Newtek Small Business Finance, Inc.	11,472
New York Business Development Corporation	6387
FC Marketplace, LLC (dba Funding Circle)	5945
LendingClub Bank, National Association	5463
Harvest Small Business Finance, LLC	5308
CDC Small Business Finance Corporation	4078
BSD Capital, LLC dba Lendistry	3516
Itria Ventures LLC	3089
Hope Enterprise Corporation	2780
Fountainhead SBF LLC	2754
DreamSpring	2450
CRF Small Business Loan Company, LLC	2392
Fund-Ex Solutions Group, LLC	1387
Montana Community Development Corp.	1184
Mortgage Capital Development Corporation	1120
LiftFund, Inc.	1034
Opportunity Fund Community Development	978
Prestamos CDFI, LLC	935
Centerstone SBA Lending, Inc.	897
Trenton Business Assistance Corporation	853
Colorado Enterprise Fund	777
Arkansas Capital Corporation	771
Grow America Fund, Incorporated	704
Colorado Lending Source, Ltd.	611

B2. Online bank FinTech lenders

Depository financial institutions that extensively rely on FinTech for their operations.

Lender	PPP loans
Cross River Bank	192,652
Celtic Bank Corporation	146,792
WebBank	75,837
Capital One, National Association	15,661
Live Oak Banking Company	11,020
American Express National Bank	6942
The Bancorp Bank	1287
Ally Bank	921
Axos Bank	851
FinWise Bank	698
First Internet Bank of Indiana	445
TIAA Bank, A Division of	272
Green Dot Bank	17

B3. FinTech lenders, alternative definition

Lenders flagged as FinTechs by the SBA on August 8, 2020 or their partner bank.

Lender	PPP loans
Cross River Bank	192,652
Kabbage, Inc.	160,897
Celtic Bank Corporation	146,792
WebBank	75,837
Readycap Lending, LLC	34,149
Intuit Financing Inc.	18,467
Fundbox, Inc.	13,543
FC Marketplace, LLC (dba Funding Circle)	5945
Fountainhead SBF LLC	2754
The Bancorp Bank	1287

B4. Rotemberg weights

Measures of the relative importance of the "shifters" Goldsmith-Pinkham et al. (2020).

Name	Bank RSSD	Rotemberg weight
Independent Bank	122,854	0.32
First Interstate Bank	659,855	0.3
Manufacturers And Traders Trust Company	501,105	0.28
Td Bank, N.A.	497,404	0.27
First National Bank Of Pennsylvania	379,920	0.24
Synovus Bank	395,238	0.22
First Horizon Bank	485,559	0.22
Citibank, N.A.	476,810	0.19
First-Citizens Bank And Trust Company	491,224	0.18
Midfirst Bank	595,270	0.18
First Midwest Bank	1,007,846	0.15
Popular Bank	2,736,291	0.15
Bbva Usa	697,633	0.15
Tcf National Bank	266,271	0.18
U.S. Bank National Association	504,713	0.24
Fifth Third Bank, National Association	723,112	0.28
Woodforest National Bank	412,751	0.33
Wells Fargo Bank, National Association	451,965	0.42
Capital One, National Association	112,837	0.44
Regions Bank	233,031	0.46
Bank Of America, National Association	480,228	2.23

Appendix C. Variable definitions

Variable	Source	Description
Frac Nonbank	SBA PPP Database	Fraction of unregulated financial institutions (nonbanks).
Frac Online Bk	SBA PPP Database	Fraction of regulated online banks with FinTech focus (generally with only 1 administrative branch).
Total FinTech PPP Fraction	SBA PPP Database	Fraction from either nonbank or online bank PPP lenders.
Loan Amount	SBA PPP Database	Approved amount of loan.
Jobs supported	SBA PPP Database	Number of jobs supported by PPP loan.
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 with <500 employees, 2017
PPP/SBA 7(a)	SBA PPP and 7(a) databases	Ratio of PPP loans to SBA 7(a) loans from 2018 to 2019, by NAICS 5-digit industry
Fraction of 7(a) loans from FinTech	SBA 7(a) data	Fraction of 7(a) loans where lender name matches a PPP FinTech lender
CA UI Claims	State of California	Number of unemployment insurance claims (California)
CA PUA Claims	State of California	Number of pandemic unemployment assistance claims (California)
Success During COVID	SBPS	Avg response to “Overall, how has this business been affected by the Coronavirus pandemic?” (5-pt scale)
Pct Denied PPP	SBPS	Share receiving PPP divided by share applying for PPP
EIDL	SBPS	Share applying for EIDL
SBA Forgiveness	SBPS	Share applying for SBA loan forgiveness
Federal Assistance	SBPS	Share applying for federal assistance
State/Local Assistance	SBPS	Share applying for state/local assistance

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