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ABSTRACT

New technology promises to expand the supply of financial services to borrowers poorly served by the banking system. Does it succeed? We study the response of FinTech to financial services demand created by the introduction of the Paycheck Protection Program (PPP). We find that FinTech is disproportionately used in ZIP codes with fewer bank branches, lower incomes, and a larger minority share of the population, as well as in industries with little ex ante small-business lending. Its role in PPP provision is also greater in counties where the economic effects of the COVID-19 pandemic were more severe. To understand whether these differences arise because certain groups are switching from traditional banks to FinTech or if they are being newly served by FinTech, we study whether FinTech-enabled PPP loans were more widespread in areas with fewer traditional loans. Using the predicted responsiveness of traditional banks to the program as an instrument, we show that borrowers were more likely to get a FinTech-enabled PPP loan if they were located in ZIP codes where local banks were unlikely to originate PPP loans.

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1 Introduction

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

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

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

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

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

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

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

Our primary question is whether specialized FinTech lenders respond differently than traditional banks to the demand for PPP. This question speaks directly to the impact of including FinTech lenders when using banks as intermediaries to provide government services. Furthermore, FinTechs are a growing share of the financial industry, so this study helps us understand how access to financial services changes as a result of their expansion.

We have three main findings. First, we show that during Phase 1 of the program, when traditional banks were most constrained, FinTech lenders provided more PPP loans to areas with a worse economic shock while traditional banks provided less. Second, we show that borrowers with less local access to the traditional banking system — as proxied by the number of bank branches, for example — were more likely to get FinTech-enabled PPP loans. Finally, we use a Bartik-style instrument to show that at least part of the difference in borrower composition was because applicants substituted to FinTech when traditional banks were not available. In areas where our instrument predicts lower traditional bank PPP lending, FinTechs originate more PPP loans per business. However, we estimate less than one-for-one substitution between banks and FinTech lenders, suggesting that FinTechs do expand access to the PPP program but do not fully close the gap in financial services across regions.

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

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

Our findings support the view in the popular press that traditional banks base their PPP originations on past relationships and are geographically constrained by the location of their physical branches, unlike FinTech which is mainly online and where prior relationships are less relevant. Comparing ZIP codes located in the same county, we find that a larger fraction of traditional bank PPP loans were originated to applicants in areas with more bank branches. Relative to FinTechs, traditional banks also provided a higher fraction of PPP loans to firms in industries with stronger ties to the banking system, as proxied for by ex ante demand for SBA loans relative to new PPP demand.

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

We find that there are fewer FinTech PPP loans per business in ZIP codes where local banks are more responsive. This finding implies that borrowers respond to a lack of bank PPP provision by somewhat (but not fully) substituting to these other types of financial institutions. It is important to note that we find evidence on substitution despite the fact that it is harder to get authorized for extending government subsidies for unregulated FinTech lenders; and, therefore, some FinTech lenders in our sample were granted authorization only during the last week of the Phase 1 of the PPP.

The incentives in play for PPP loan origination are different from standard credit. Although technically termed "loans," PPP funds are forgiveable in many circumstances and the lender does not bear any credit risk. Therefore, the differences in the response of FinTech and traditional banks in the PPP context may not map directly to the differences in standard credit provision. Our results speak to the differences between FinTechs and traditional banks' use of relationships to allocate credit and their use of new technology, but not to differences in credit evaluation and risk management. Nevertheless, the PPP program sheds light on how differences in technology and reliance on relationships between FinTech and traditional banks affect financial intermediation.

The rest of the paper is organized as follows. Section 2 reviews the literature on FinTech lending. Section 3 describes the PPP, discusses the data collection process and presents summary statistics. In Section 4, we present our main results on geography of online and nonbank lending. Section 5 addresses whether ZIP codes with less bank branches had more PPP loans by FinTech lenders, controlling for local demographics. In Section 6, we calculate predicted responsiveness of banks to the PPP and then test whether borrowers were more likely to get a FinTech-enabled loan if they are located in ZIP codes where local banks were unlikely to originate PPP loans. Section 7 concludes.

2 Literature Review

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

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

Although many purely online FinTech lenders started as peer-to-peer lenders extending only personal loans, they have also moved to direct small-business lending. As Stulz (2019) discusses, two well-known FinTech firms, LendingClub and Kabbage, make traditional small-business loans through a banking subsidiary or a funding bank partner. Buchak et al. (2018) show that there has been a dramatic growth in online FinTech lenders of mortgage loans post-financial crisis. FinTech banks have also been competing aggressively on the funding side of the financial institutions' balance sheet. Abrams (2019) points to the rapid growth in deposit contracts offered by online banks in the past decade: online banks now comprise four of the 30 largest banks by deposits, pay higher deposit rates, and have about the same amount of market power over their depositors as midsize banks do. Given the way the PPP program is struc-

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

tured, having an existing relationship with a bank, even through a simple commercial deposit account should matter.

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

Lastly, we also contribute to the literature on government interventions – especially, directed lending programs. Such programs can run in a form of a direct subsidy (e.g., Banerjee and Duflo (2014) using data from India) or an indirect subsidy as in a loan guarantee (e.g., Claire, Sraer and Thesmar (2010) using data from France). PPP is also a directed lending program, where the Small Business Administration offered guaranteed and potentially forgivable loans to small businesses. But borrowers apply

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

for and receive loans through the system of financial institutions. Therefore, the role of these institutions in this process is essential. Some contemporaneous papers have also studied the PPP program. Cororaton and Rosen (2020) study public firms that got funding through the PPP and received significant media outrage as the program aimed to help small businesses. They document that only 13% of the eligible public firms, which is half of the public firms, end up participating. Using preliminary data, Granja, Makridis, Yannelis and Zwick (2020) examine whether areas that were more severely hit by the Covid pandemic, as measured by declines in hours worked or business shutdowns, end up getting more allocations. Barrios, Minnis, Minnis and Sijthoff (2020) develop a payroll-based framework and provide preliminary analyses that the state-level funds, which were granted till May 1st, were allocated as predicted by their framework. Bartik, Bertrand, Cullen, Glaeser, Luca and Stanton (2020) study the effects of PPP on small businesses using a representative national survey.[8] In this paper, we focus on the differential effect of nonbanks and online banks in channeling PPP funds.

3 Payroll Protection Program and Data

The Paycheck Protection Program (PPP), which authorized up to $659 billion (in two Phases[9]) toward job retention by small businesses, is established by the CARES Act. This program provides loans to small businesses and eligible nonprofit organizations to pay up to 8 weeks of payroll costs including benefits, interest on mortgages, rent,

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

[9] $349 billion was distributed in Phase 1.

and utilities.[10] With already over $521 billion approved —about 4.9 million loans passed through 5,453 financial institutions— the PPP has been one of the largest economic stimulus programs in U.S. history. According to data reported by program participants, it has supported over 51 million jobs, clearly a majority of the small businesses' employment.

The program is administered by the Small Business Administration (SBA) but loans are allocated through eligible financial institutions. These eligible institutions include any SBA 7(a) lender, federally insured depository institutions or credit unions, or any other lender that is approved by the SBA and enrolled in the program. Lenders neither charge any fees nor ask for collateral to grant these small business loans. Loans issued prior to June 5 have a maturity of 2 years while the ones issued after June 5 have a maturity of 5 years. These PPP loans carry an interest rate of 1% but any loan payment is deferred for six months. Most importantly, the loans are fully forgiven if the funds are used for (at least 60%) payroll costs, interest on mortgages, rent, and utilities. The majority of loans granted were for less than $150,000, with the overall average loan size being $107,000.

Our main data source is the database of PPP loans released by the Small Business Administration (SBA) following an agreement between the Small Business Committee of the U.S. Senate and the Department of Treasury. Under the agreement, the SBA released loan-level data on all PPP loans. Data include some characteristics of borrowers and loans. For loans with a value above $150,000, borrower names are available, but the loan amounts are grouped into bins. For smaller loans, the exact dollar amount is available but not the borrower names. The borrower's industry information is available at the 6-digit NAICS level for all loans. The SBA also provided

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

the names of the financial institutions (but no other identifiers) that facilitated the loan applications and distributions.[11]

We match this loan-level data to bank identifiers from the FFIEC using the lender names provided.[12] Most of the names are matched using automated name matching.[13] Lenders which we are not able to match automatically are a combination of non-bank lenders, banks that have duplicate names, and banks that have idiosyncratic names. We therefore hand-match all PPP lenders who originate over 750 PPP loans, classifying separately non-bank lenders and banks which do not have a unique match in the FFIEC database. This procedure allows us to match over 85% of all PPP loans in the sample. The remaining lenders are mostly small community banks with non-standard or non-unique names.

After matching the PPP data to the relevant financial institutions, we match these to institutional information for lenders that are deposit-taking banks. We 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. Then we classify lenders into five categories: Large banks (with assets above $20bn), small banks (with assets below $20bn), credit unions, nonbanks and online banks. Note that nonbanks refer to non-depository financial institutions. Online banks are defined to be banks with only a single branch (Abrams, 2019).[14] In addition, we will also use a simpler three-part classification: online banks,

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

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

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

[14]Measuring online banks based on number of loans per branch yields very similar results.

nonbank lenders, and all remaining traditional banks and credit unions. We describe both online banks and nonbank lenders as FinTechs, but because of differences in regulatory treatment we analyze them separately.[15]

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

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

We measure the magnitude of the economic shock by county using data from the Opportunity Insights *Track the Recovery* web site (Chetty, Friedman, Hendren and Stepner, 2020). We focus on two main measures. First, we measure the four-week change in unemployment claims by county as of April 11, 2020. This measure covers

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

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

the last week before unemployment started rising until the peak level of unemployment claims nationally. Second, we measure the average of the daily count of COVID cases by county in March. See Chetty et al. (2020) for more details on these measures.

Summary Statistics by ZIP codes are shown in Table 1. The summary statics weight all ZIP codes equally. Since we do not have loan amounts for all types of loans — only those with a value below \$150,000 — our analysis focuses on the number of PPP loans rather than on their dollar amount.[17] There are 134 PPP loans in a given ZIP code, where median income about little under \$60,000, only 17% of the population commute at least 45 minutes per day to work, 83% is white, on average. In a typical ZIP code with PPP loans, there are 4.5 branches with a higher standard deviation though. Also, note that bank branch summary statistics are shown only for ZIP codes with a non-zero number of branches. On average, total population in a given ZIP code in our sample is about 4,500, with 231 establishments. These areas also had 1% average COVID case rate and 3% unemployment growth.[18]

4 The Geography of Online and Nonbank Lending

Figure 1 shows the number of PPP loans by lender type over time. The X-axis of this figure shows the approval date and the Y-axis shows the number of PPP loans approved on each date by lender type. There is a gap between April 16, when PPP Phase 1 ended, and April 27, when Phase 2 began.

Media reporting during PPP Phase 1 suggested that smaller banks were better able to process PPP loans than larger banks. The evidence in the upper panel of this figure supports this view: During the initial weeks of PPP Phase 1, there were

[17]Figure 6 shows the average loan size, as measured by self-reported jobs retained, for both types of loans. On average, online banks and nonbanks originate smaller loans than traditional banks do.

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

more PPP loans arranged by small banks than by large ones.[19] The difference shrank towards the end of Phase 1, and by late Phase 2, large banks were responsible for more PPP lending than small banks were.

The lower panel of Figure 1 shows the fraction of PPP loans originated by online banks and nonbanks. Overall, online banks were responsible for about 10% of PPP loans and nonbanks for about 5%. The share of loans from these institutions was higher during the later weeks of Phase 1, and particularly high towards the end of Phase 2.[20]

Before we present the geographic distribution of PPP loans by traditional and Fintech lenders, we compare our measure of online lending to an independent measure of interest in online PPP lending based on Google searches for online PPP lenders. Specifically, we use Google Trends to calculate, at the state level, variation across states in searches for the phrase "apply for ppp loan online" from March 1, 2020 to July 10, 2020. States with few searches are excluded from the Google Trends data.[21] Figure 2 shows the relationship between Google searches for online lending and our measure of actual PPP loans, with missing states located at zero. The relationship is positive and statistically significant whether or not we include states that have too few searches to include.

Next, we turn to the geographic distribution of relative PPP loan provision by online banks and nonbanks. The specifications in Table 2 explore the geographic correlates of PPP loan provision. Our first question is whether FinTech PPP loans

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

[20] The share is highest of all in the first week of May, 2020, but this is not terribly meaningful because of the low number of loans approved overall at this time.

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

flowed unconditionally to the areas that needed it most in both periods, and PPP lending is different for traditional banks versus online banks nonbank financial institutions. To measure which areas were most in need of PPP loans, we use county-level variables collected by Chetty et al. (2020), the increase in unemployment claims rate (between the months of March and April) and the average COVID-19 case rate. Our other variables are measured at the ZIP code level. We control for the log number of establishments by ZIP code to avoid a mechanical relationship between the number of establishments and the number of loans. Regressions are run at the ZIP code-level and estimates are weighted by total PPP loans by ZIP code. Robust standard errors are reported. Our dependent variable is the log of total PPP loans by traditional banks vs. nonbank/online lenders.

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). In fact, traditional banks provided *fewer* PPP loans to counties which needed it more, along both measures. By contrast, online banks and nonbanks did provide more loans to areas with a greater increase in unemployment during Phase 1. While regions with a higher COVID-case rate did not get more PPP loans, they did not not get less, either.[22] During Phase 2, PPP loans flowed towards areas that needed more assistance both from traditional banks and from online banks/online lenders. Supporting the widely-reported problems with banks' ability to provide PPP loans to areas that needed it during Phase 1 of the program, these findings would seem to indicate that online and nonbank lenders were better able to respond to local demand, at least initially.

Figure 3 is a county-level graph showing the fraction of PPP loans coming from

[22]When we add more regional controls variables, the sign on the case rate becomes negative for online lenders and remains negative for traditional banks. But for now, we are interested in the *unconditional* relationship between case rate and PPP loan provision.

each type of institution for the entire United States. Here, we consider a combination of Phase 1 and Phase 2 loans. There are clear patterns visible in this figure. Major metropolitan areas, such Atlanta, Miami, Houston and Chicago, as well as both coasts, have a high fraction of their PPP loans originated both by nonbanks and by online banks. Urban parts of New Mexico, Colorado and Arizona also have significant nonbanks and online bank PPP loan origination.

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

Figure 4 shows the distribution of PPP loans for ZIP codes in Cook County, which includes most of the Chicago metro population. We are interested in understanding the distribution of online and nonbank loans in relation to demographic differences in ZIP codes within the metropolitan area. As shown in the upper-left panel of this figure, Cook County is characterized by large differences in income by ZIP code. The North Shore is high-income and 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 online and nonbank lenders as opposed to from traditional banks and credit unions. The next three panels of Figure 4 show the fraction of PPP loans which we classify as coming from these categories. Businesses in the richer ZIP codes of Chicago mostly get their loans from traditional banks and credit unions, whereas the lower-income areas get a higher fraction of their loans from FinTechs and nonbanks. We have created similar maps for other major metro areas and found similar patterns. Moreover, this relation between online/nonbank lending and ZIP demographics is significant using linear regressions as well.

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

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

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

5 Branch Distance and Nonbank/Online Lending

Do ZIP codes with fewer bank branches get more online and nonbank loans when we control for local demographics? Table 3 shows how the PPP lending share varies -i.e., fraction of PPP lending by online banks, nonbanks, or banks- with the log number of branches in each ZIP code. Columns 1-3 of this table show the relationship between log bank branches with no controls other than county fixed effects.[23] More bank branches is, overall, associated with a lower online or nonbank share of PPP loans. These coefficients decrease somewhat, but remain large, after controlling for local demographic factors. We control for median income, the fraction of white population in a ZIP code, and the fraction of population with a commute above 45 minutes. The coefficients on these demographic variables also make sense given the findings so far. Within a county, areas with lower incomes, longer commutes, and more non-white people have a larger online and nonbank share of PPP loans.

The distribution of firms may vary by ZIP code, leading to differences in firm risk and potentially in demand for nonbank credit. To test how this might affect our results, Table A1 in the Appendix shows results from similar specifications at the *loan* level. Loan level specifications allow us to control for differences in borrower characteristics. All the specifications in this table control for borrower industry, for example. Since we use 6-digit NAICS industries, the NAICS industry likely proxies for many types of borrower differences. We also add controls for average establishment size and local demographics. Throughout, the effect of bank branches on the online and nonbank share remains negative and statistically significant, and it does not change much even after including NAICS6 fixed-effects.

As also discussed above, the economic effects of the COVID-19 epidemic were

[23] This variable is measured as log(1+bank branches) so that we can include ZIP codes with no branches.

unevenly distributed during the time period we study. As we show in Table 2 for two phases separately, borrowers in areas with a worse shock are more likely to take PPP loans. Next we explore whether the presence of local bank branches mediated the shock. To answer this question, we again use data on the rise in unemployment at the county level (between the months of March and April) and focus on its interaction with the log bank branches.

Table 4 starts with how unemployment affected total PPP lending and non-bank/online lending over both phases of PPP together. In the average county, unemployment claims per 100 people in the labor force grew by about 3 (from about 1 to about 4), but the increase in the unemployment claims rate was unevenly distributed. Counties where the unemployment rate grew by one point more had about 0.1 log points higher PPP applications as well. These areas also had a higher share of PPP coming from nonbanks and from online lenders, indicating that these types of lenders effectively served areas with greater economic shocks.

In Columns (2) and (4) of Table 4 we add county fixed effects to study how the economic shocks differentially affected ZIP codes within counties, depending on how many bank branches they had. Overall, in areas with fewer bank branches, the effect of the shock on the fraction of nonbank and online lending was larger. Indeed, adding the unemployment-by-branches interaction term drives out the main effect of bank branches, indicating that having branches in itself does not lead to more online PPP loans absent an economic shock.[24]

The statistics so far have provided evidence that in lower-income areas and in areas with fewer banks, more borrowers turned to online and nonbank loans for their

[24]Appendix Table A2 repeats the findings in Table 4 using a different measure of the economic shock — the average COVID-19 case rate during the month of March. The results in this table confirm the findings in Table 4, but are somewhat noisier, and not all the estimates are statistically significant.

PPP. But, we are also interested in directly answering the question of whether firms with less *ex ante* exposure to the formal banking system were more likely to turn to these types of lenders.

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

These estimates are shown in Table 5. As shown in Columns (1) and (3) of this table, businesses in industries with a higher PPP demand shock *relative* to the SBA 7(a) lending quantity were more likely to go online or turn to nonbanks. Differences in industry exposure to COVID could potentially affect their demand for PPP loans. To control for this, we add fixed effects at the NAICS 2-digit level and study differences in loan demand within these category. NAICS 2-digit codes control for broad industry groupings, such as retail stores, wholesale trade, etc., which partially control for direct industry exposure to the COVID shock. When we add these controls, the coefficients on the SBA loan access measure increase and remain highly statistically significant.

These results show that banks base their lending on past relationships and constrain themselves around their branches. FinTech lenders do not have geographic constraints based on the presence of loan officers or physical bank branches. Despite this, there are a few reasons to think that relationships, or something akin to relationships, might matter for FinTechs. First, borrowers might not know about the possibility of getting a PPP loan through an online bank unless they have done it before. Therefore, areas with many FinTech borrowers in the past might be disproportinately served by FinTech lenders during the PPP program. Second, small businesses might use online banks for other types of financial services, such as deposits or credit cards. Such borrowers might also trust the same firms to supply PPP loans for them. In both cases, we would expect areas with a large historical FinTech presence to have more PPP loans as well.

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

The estimates in Table 6 show the relationship between the share of 7(a) loans in each ZIP code coming from FinTech lenders and the share of PPP loans coming from them. We find that geographic persistence matters for FinTech lenders, but it is not the only important factor. On the one hand, the estimated effect of 7(a) lending from FinTechs on the online share of PPP loans is statistically significant at the 1% level and the coefficient increases in magnitude in estimates that include control variables. On the other hand, the point estimate is economically very small – 0.018 without controls and 0.023 including controls. The coefficients on log bank branches are not driven out when we include the FinTech fraction of 7(a) loans as a control variable; the estimates here are only slightly smaller than the estimates in Table 3. Finally, there is no estimated relationship between the share of 7(a) loans from FinTech lenders and the share of PPP loans from nonbank lenders, probably because nonbank lenders do not play an important role in the 7(a) program.

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

6 Predicting Traditional Banks' PPP Provision

What explains why areas with more bank branches have a lower share of online PPP loans? We can think of at least two ways of explaining these findings. First, banks might lend to borrowers only in the region where their branches are located, whereas online and nonbank lenders might lend everywhere. Therefore, differences in where banks are willing to lend could mechanically change the fraction of all loans coming from online banks/nonbanks even as the *level* of PPP loans from online/nonbank lenders is the same everywhere.

Second, if banks are unwilling to lend far from their branches, borrowers could substitute between banks and nonbanks or online banks. Moreover, banks' unwillingness to lend to borrowers far away could have increased due to the COVID-19 shock. As Granja, Leuz and Rajan (2018) find, lending distance for small business loans is cyclical, with the distance decreasing significantly during crises. This substitution would lead to a change in the number of PPP loans per business, as well as the change in fraction, which we observed. On the other hand, if borrowers *perfectly* substitute between banks and non-banks, then in principal it is possible that a reduction in bank lending would not lead to an overall reduction in the provision of PPP loans.[25]

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

Our bank PPP lending measure is created in two steps. First, we measure PPP loans per bank branch (PPP loans divided by the number of bank branches) at the bank level nationally. We calculate this measure separately for each bank and each county, dropping each county's own branches and loans in order to create a "leave-one-out" measure. In this way, we create a measure akin to a shift-share shock (Bartik, 1991), where we quantify the degree of responsiveness, at the bank level, to the PPP

[25] A third possible reason is that borrower characteristics vary across regions. For example, maybe high-tech firms are more likely to be located in areas far from bank branches. Since the estimates did not change in Table A1 when borrower industry fixed effects were included, we do not believe this explanation is as likely as the others.

program. In the second step, we calculate the average responsiveness by ZIP code of banks located there. This yields a prediction for the amount of PPP lending that will take place in each ZIP code. We take the log of this measure to calculate the log predicted number of PPP loans by ZIP code.[26]

As noted, the purpose of measuring PPP responsiveness using bank characteristics is to predict PPP lending independent of the magnitude of the COVID-19 shock. Table A3 in the Appendix verifies that the predicted lending measure is independent of our two proxies for the size of the COVID shock — the increase in the unemployment claims rate from March 15 to April 11, and the average COVID case rate in March. Ideally, we would measure these variables at the ZIP code level and use specifications with county fixed effects. Since these variables are only available at the county level, this table uses Commuting Zone fixed effects instead. We also include specifications which control for the number of bank branches per ZIP code, since the degree of bank competition could be correlated with unemployment and also affect banks' degree of responsiveness.

An implicit assumption of this approach is that banks are more likely to make PPP loans in ZIP codes where their branches are located. Table A4 of the Appendix shows that this is true. Column 1 shows the results of bank-by-ZIP code level specifications for each ZIP code where banks have branches. We also show results from a specification with ZIP code fixed effects in Column 2. The large positive coefficient in this column means that, within ZIP code, banks with more branches originate more PPP loans. Finally, Column 3 adds bank fixed effects, so the results are driven by within-bank, cross-ZIP code variation. The coefficient does not vary much across columns.

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

Next, we verify that in ZIP codes with more responsive banks, more PPP lending is provided overall. These results are shown in Appendix Table A5. Throughout, we control for the total number of bank branches. The variable of interest is labeled "Predicted Loans" and it measures the log predicted number of PPP loans by ZIP code. To reduce the influence on our measure of online lenders which have many loans per branch, we include Winsorized versions of the measure. The coefficients on the Winsorized measures are larger than the un-Winsorized ones, as we expect. Therefore, we use the predicted PPP measure that is Winsorized at the 95th percentile.[27]

If online banks and nonbank loans fully compensated for a lack of bank loans in a ZIP code, then predicted bank PPP lending would not affect overall PPP lending. The estimates in Table A5 show that predicted bank PPP lending does impact overall PPP lending, however, so these online/nonbank loans are not perfect substitutes for bank loans.

Table 7 shows the effect of predicted PPP bank lending on the fraction of loans from online and nonbank lenders. ZIP codes with more responsive banks have a lower fraction of loans from online banks and nonbanks. This holds with and without county fixed effects, and including ZIP code level demographic controls.

As discussed at the beginning of this section, if a ZIP code has banks that do more PPP lending, that would lead to a lower fraction of online and nonbank loans even if the *number* of these loans is unchanged. To understand whether bank PPP lending affects the number of nonbank/online PPP loans, we estimate regressions with nonbank/online lending is the dependent variable. We scale PPP lending by the number of establishments in each ZIP code.

[27]Columns 2, 4 and 6 of Table A5 add county fixed effects. County fixed effects reduce the effect of the shift share measure (predicted loans), although it still remains highly statistically significant. A likely explanation for this decline in economic significance is that there are spillovers between ZIP codes within county: If one ZIP code has banks that are more responsive, they might provide PPP loans to a neighboring ZIP code with less responsive banks.

These results are shown in Table 8. In ZIP codes where local banks are predicted to make more PPP loans, there is less online/nonbank PPP lending per establishment. Both online and nonbank lending respond to the predicted amount of traditional bank PPP lending and the coefficients are of similar magnitude. This finding provides evidence that borrowers partially substitute for nonbank and online lenders when banks do not provide financial services they require.

7 Conclusion

This papers studies whether online and nonbank lenders provide access to financial services for regions and borrowers that are not served by the traditional banking system. When we compare different regions of the country, 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, online banks and nonbanks disproportionately serve industries and ZIP codes with less access to traditional finance. ZIP codes with fewer bank branches and a lower median income get more of their PPP loans from these types of new lenders. Across industries, firms in industry codes who previously got fewer SBA loans were more likely to get their PPP loans from online banks and nonbank lenders. Finally, we show that in ZIP codes where lenders did not do much PPP origination, local small businesses turned to online banks and nonbanks instead.

We have focused on online banks and nonbank lenders which do not engage in traditional banking. But traditional banks may also use technology-enabled credit scoring or loan application mechanisms. Whether they do so in a different way than specialized FinTech lenders is a fruitful area for future research.

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8 Figures

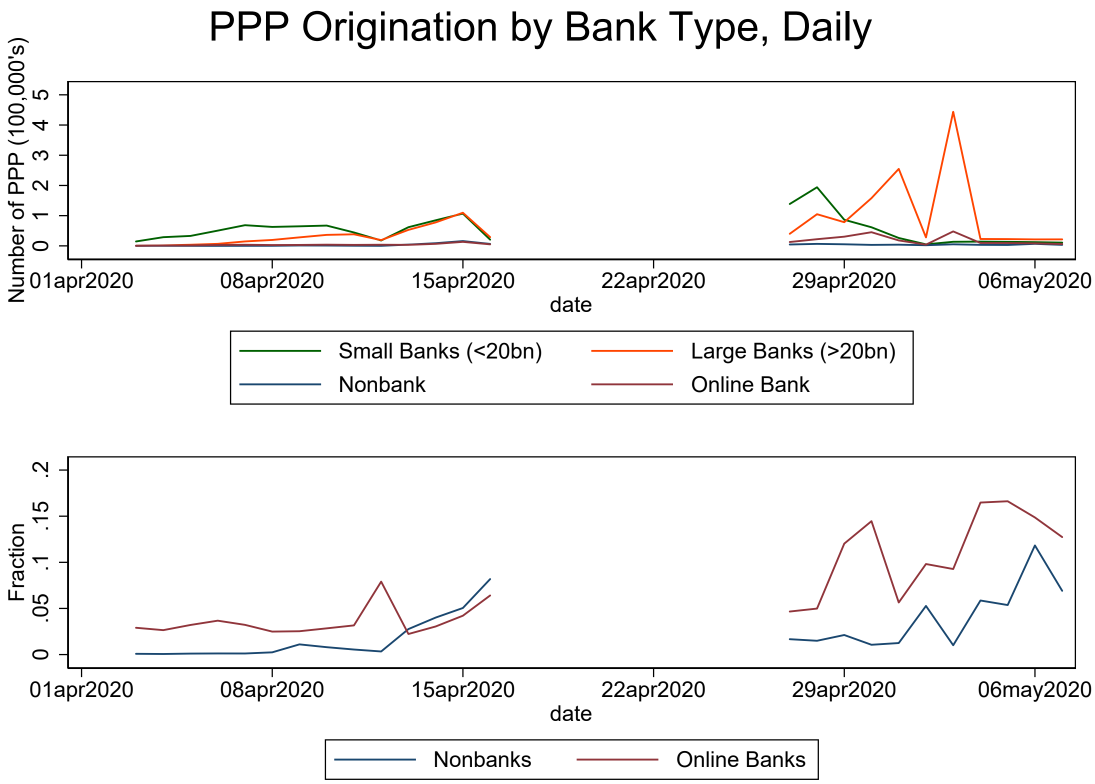


Figure 1: PPP Lending by Day and Type of Institution.

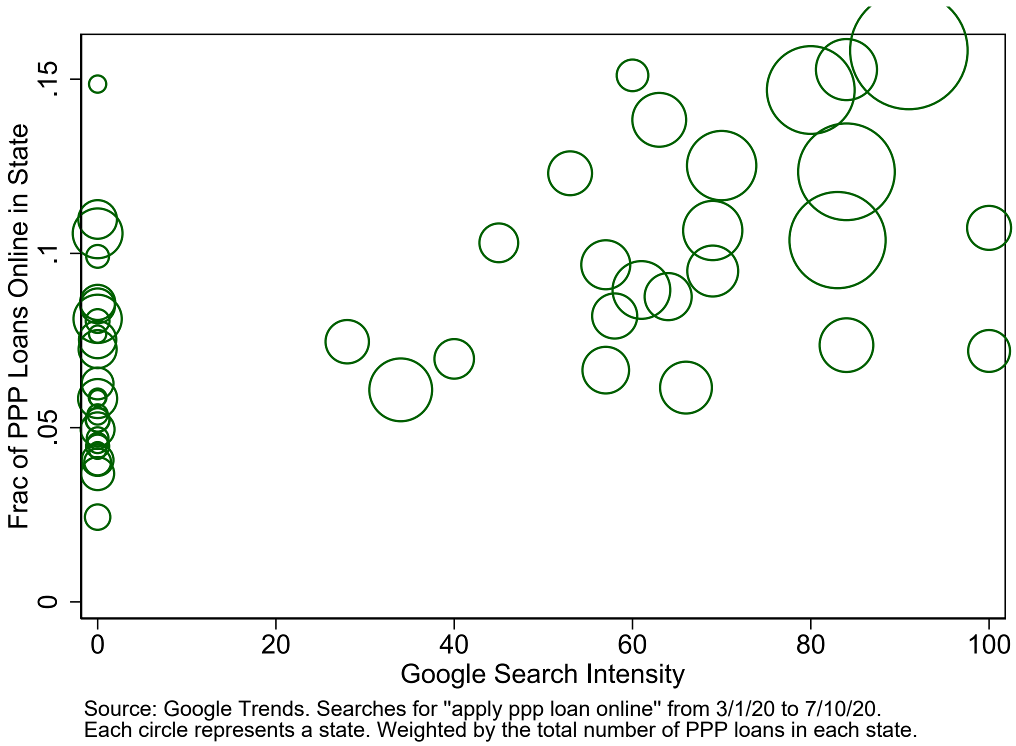


Figure 2: Google Searches for Online PPP Loans.

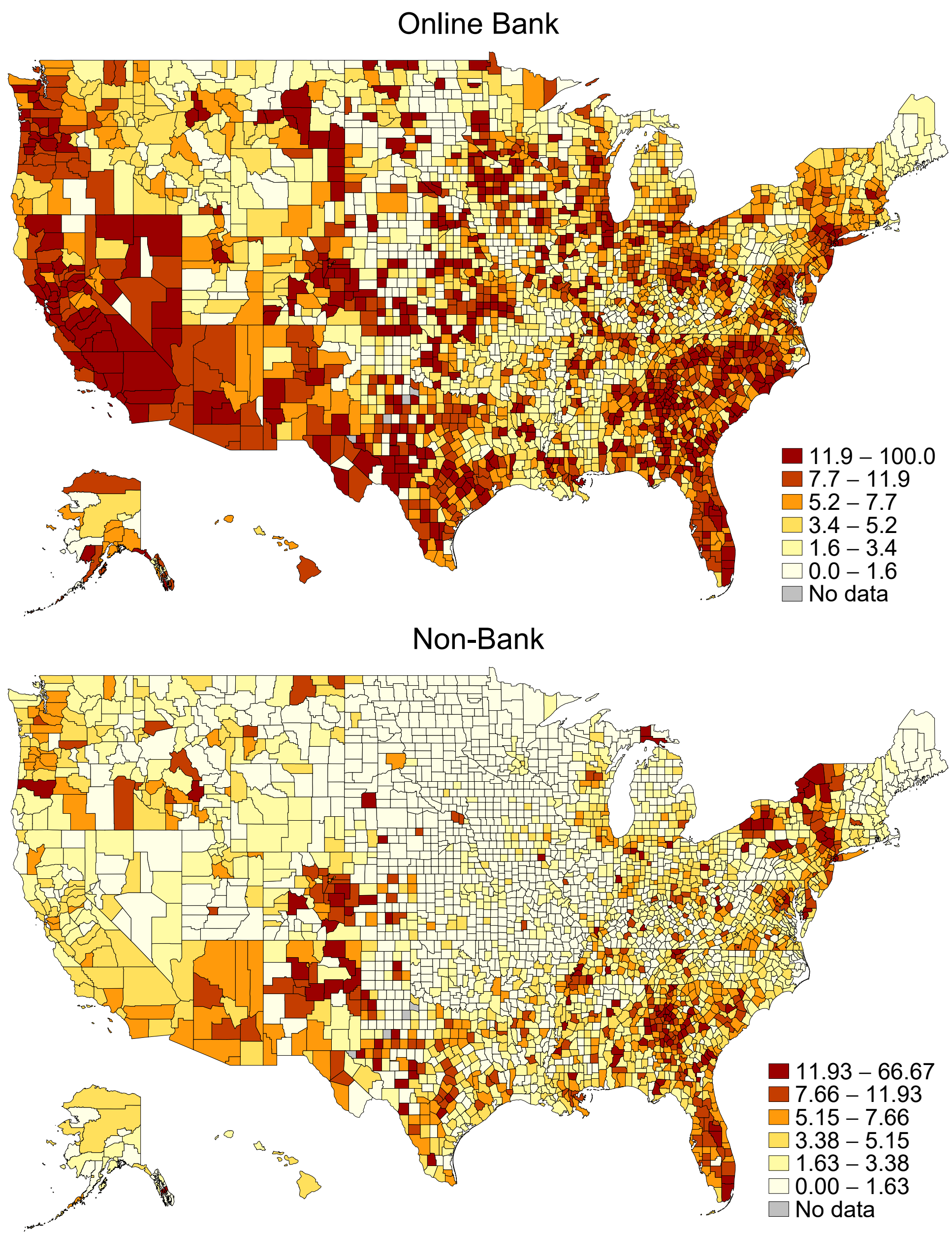


Figure 3: PPP Lending by Category, U.S.

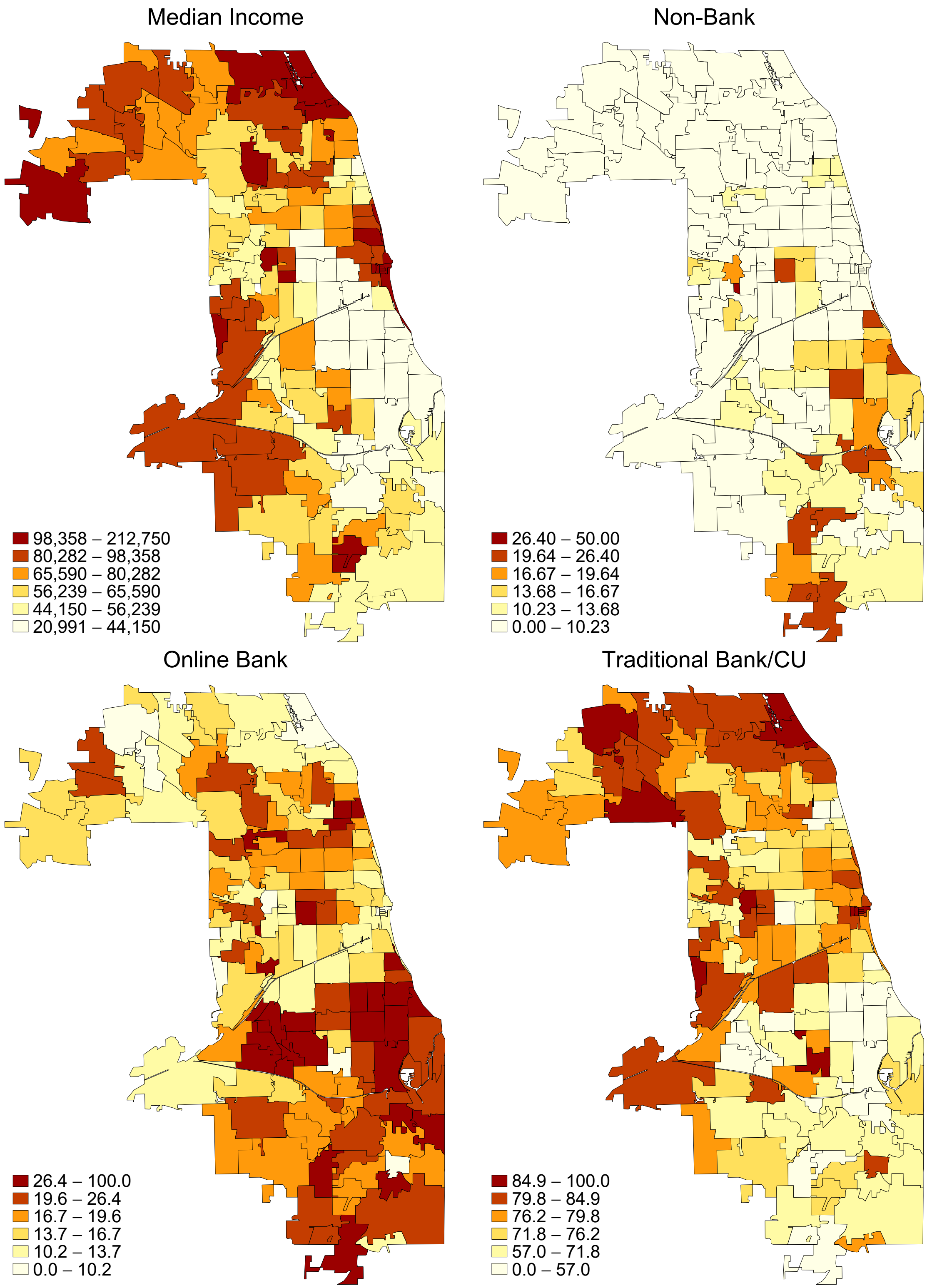
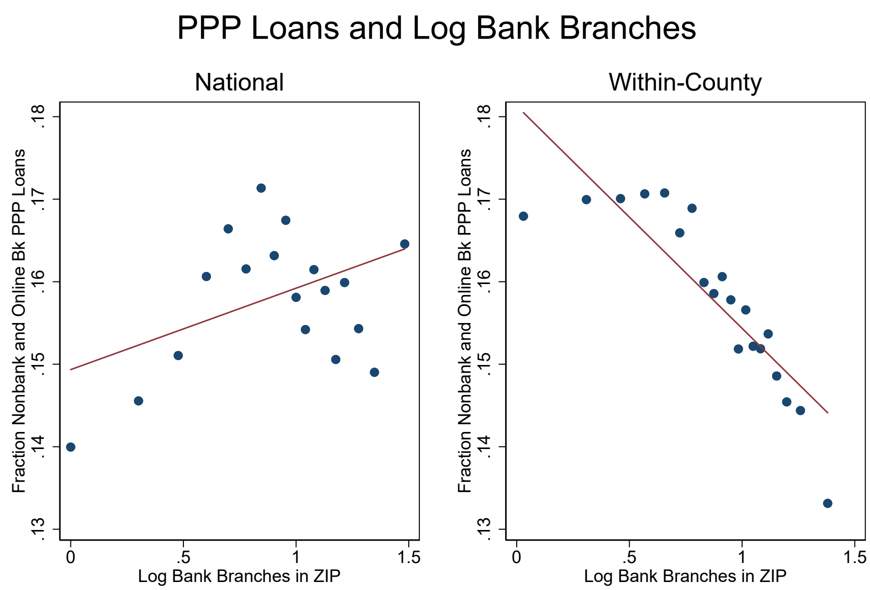


Figure 4: Lending in Chicago.



Source: Calculated from FDIC Summary of Deposits and SBA PPP Database.
Weighted by PPP loans per Zip code.

Figure 5: Lending Share and Log Bank Branches.

9 Tables

Table 1: Summary Statistics by ZIP Code

	Mean	St. Dev	5th Pctile	Median	95th Pctile	Count
Frac Nonbank	0.04	0.10	0.00	0.00	0.17	35,703
Frac Online Bk	0.08	0.13	0.00	0.04	0.28	35,703
Frac Bk/CU	0.88	0.17	0.57	0.92	1.00	35,703
Num. PPP Lns	133.66	246.54	1.00	25.00	638.00	36,552
Median Income	59,480.96	25,251.78	30,231.00	54,301.00	106,842.00	29,949
Frac. 45m+ Commute	0.17	0.12	0.02	0.15	0.40	31,115
Frac. White	0.83	0.20	0.38	0.92	0.99	31,423
Total Pop	4,569.32	6,747.11	50.00	1,313.00	19,268.00	31,487
Num. Bk Branches	4.53	4.90	1.00	3.00	15.00	19,398
Avg COVID Case Rate	0.01	0.02	0.00	0.00	0.02	35,628
Unemp. Growth	2.94	1.78	1.14	2.63	5.98	17,111
Num. Estabs	230.62	404.12	4.00	45.00	1,072.00	33,883

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

Table 2: Geographic Correlates of PPP Provision

	(1) Log PPP Trad. Bk Phase 1	(2) Log PPP Online/Non-bk Phase 1	(3) Log PPP Trad. Bk Phase 2	(4) Log PPP Online/Non-bk Phase 2
Avg Case Rate	-3.18***	-0.40	1.02***	4.52***
	(0.21)	(0.25)	(0.085)	(0.17)
Change in Unemployment	-0.075***	0.078***	0.041***	0.12***
	(0.0060)	(0.0084)	(0.0031)	(0.0082)
Log Establishments	0.92***	1.03***	1.03***	1.07***
	(0.0068)	(0.014)	(0.0038)	(0.0076)
Constant	-1.28***	-4.88***	-1.62***	-3.68***
	(0.042)	(0.091)	(0.023)	(0.047)
Observations	14113	7039	15154	10760
R^2	0.737	0.552	0.887	0.746

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

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

	(1) Online PPP Fraction	(2) Nonbank PPP Fraction	(3) Bank PPP Fraction	(4) Online PPP Fraction	(5) Nonbank PPP Fraction	(6) Bank PPP Fraction
Log Branches	-0.0042***	-0.0075***	0.012***	-0.0028***	-0.0053***	0.0082***
	(0.00047)	(0.00038)	(0.00075)	(0.00048)	(0.00035)	(0.00072)
Log Med. Inc				-0.0036*	-0.00069	0.0043
				(0.0020)	(0.0014)	(0.0031)
Frac Commute 45+m				0.064***	0.068***	-0.13***
				(0.0081)	(0.0055)	(0.012)
Frac White				-0.053***	-0.071***	0.12***
				(0.0047)	(0.0036)	(0.0076)
Constant	0.11***	0.068***	0.82***	0.18***	0.11***	0.71***
	(0.00095)	(0.00081)	(0.0016)	(0.020)	(0.013)	(0.030)
Observations	34999	34999	34999	29456	29456	29456
R^2	0.641	0.572	0.662	0.669	0.648	0.712
County FEs	X	X	X	X	X	X

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

Table 4: Increases in County Unemployment and PPP Origination

	(1) Nonbank PPP Fraction	(2) Nonbank PPP Fraction	(3) Online PPP Fraction	(4) Online PPP Fraction
Unemp. Chg	0.0069***		0.012***	
	(0.0015)		(0.0019)	
Log Branches		-0.00075		0.0047
		(0.0054)		(0.0054)
Unemp. Chg × Log Branches		-0.0046**		-0.0047***
		(0.0018)		(0.0015)
Constant	0.034***	0.071***	0.079***	0.13***
	(0.0047)	(0.0021)	(0.0063)	(0.0024)
Observations	16743	16743	16743	16743
R^2	0.075	0.581	0.087	0.660
County FEs		X		X

ZIP code level specifications showing the relationship between the share of online/nonbank PPP lendincg and ZIP code level statistics interacted with the change in unemployment. Robust standard errors. Estimates are weighted by PPP loans per ZIP code. Data calculated from the FDIC Summary of Deposits database and SBA PPP loan data.

Table 5: Industry Differences in 7(a) Lending

	(1)	(2)	(3)	(4)
	Online PPP Loan	Online PPP Loan	Nonbank PPP Loan	Nonbank PPP Loan
Log(PPP/SBA 7a)	0.011***	0.016***	0.0045***	0.0064***
	(0.00028)	(0.00033)	(0.00020)	(0.00024)
Constant	0.063***	0.045***	0.040***	0.032***
	(0.0011)	(0.0014)	(0.00081)	(0.00097)
Observations	3929813	3929813	3929813	3929813
R^2	0.056	0.066	0.043	0.058
Zip FEs	X	X	X	X
NAICS2 FEs		X		X

Industry-level specification showing the relationship between the online share of PPP lending and overall industry use of PPP relative to ex ante industry SBA 7(a) loans. Data calculated from SBA 7(a) and PPP data.

Table 6: Online/Nonbank PPP Lending and Previous Nonbank/Online 7(a) Lending

	(1) Online PPP Fraction	(2) Nonbank PPP Fraction	(3) Online PPP Fraction	(4) Nonbank PPP Fraction
7(a) Share	0.018***	-0.0023	0.023***	0.0028
	(0.0046)	(0.0034)	(0.0045)	(0.0030)
Log Med. Inc			-0.0039*	-0.00062
			(0.0022)	(0.0014)
Frac Commute 45+m			0.069***	0.073***
			(0.0090)	(0.0061)
Frac White			-0.052***	-0.071***
			(0.0049)	(0.0038)
Log Branches			-0.0032***	-0.0056***
			(0.00052)	(0.00039)
Constant	0.10***	0.055***	0.18***	0.11***
	(0.00052)	(0.00040)	(0.021)	(0.014)
Observations	20394	20394	19346	19346
R^2	0.701	0.597	0.726	0.684
County FEs	X	X	X	X

ZIP-level specification showing the relationship between the fraction of loans from nonbank and online bank lenders, and the fraction of 7(a) loans from such lenders between 2014-2018. Data calculated from SBA 7(a) and PPP data.

Table 7: Effect of Predicted Bank PPP on Online/Nonbank PPP Shares

	(1)	(2)	(3)	(4)
	Online PPP Fraction	Online PPP Fraction	Nonbank PPP Fraction	Nonbank PPP Fraction
Predicted PPP	-0.016***	-0.0078***	-0.014***	-0.0066***
	(0.0019)	(0.0017)	(0.0012)	(0.0013)
Log Med. Inc.	0.020***	-0.0049**	-0.0031**	-0.0013
	(0.0020)	(0.0021)	(0.0012)	(0.0015)
Frac Commute 45+m	0.14***	0.056***	0.10***	0.064***
	(0.0079)	(0.0094)	(0.0045)	(0.0063)
Frac White	-0.11***	-0.041***	-0.064***	-0.063***
	(0.0043)	(0.0051)	(0.0033)	(0.0040)
Bk Branches	-0.0065***	-0.0088***	-0.0067***	-0.0099***
	(0.0011)	(0.00079)	(0.00075)	(0.00064)
Log Pop	0.019***	0.013***	0.012***	0.0086***
	(0.00091)	(0.00066)	(0.00060)	(0.00060)
Constant	-0.17***	0.11***	0.069***	0.070***
	(0.020)	(0.023)	(0.012)	(0.015)
Observations	15479	15479	15479	15479
R^2	0.311	0.763	0.295	0.725
County FEs		X		X

ZIP code level specifications showing the relationship between the share of PPP lending from online banks/nonbanks, and the predicted level of PPP lending based on banks' overall degree of PPP lending. Robust standard errors. Estimates are weighted by PPP loans per ZIP code. Data calculated from the ZIP business patterns and SBA PPP loan data.

Table 8: Effect of Predicted Bank PPP on Total PPP Per Establishment

	(1) Online PPP/ Establishments	(2) Online PPP/ Establishments	(3) Nonbank PPP/ Establishments	(4) Nonbank PPP/ Establishments
Predicted PPP	-0.0021	-0.0043***	-0.0038***	-0.0038***
	(0.0013)	(0.0015)	(0.00089)	(0.0011)
Log Med. Inc.	0.018***	0.012***	0.00037	0.0074***
	(0.0014)	(0.0018)	(0.00086)	(0.0012)
Frac Commute 45+m	0.10***	0.063***	0.076***	0.057***
	(0.0055)	(0.0085)	(0.0032)	(0.0054)
Frac White	-0.061***	-0.031***	-0.037***	-0.045***
	(0.0030)	(0.0048)	(0.0023)	(0.0036)
Bk Branches	-0.0076***	-0.010***	-0.0061***	-0.0087***
	(0.00079)	(0.00071)	(0.00053)	(0.00052)
Log Pop	0.013***	0.0099***	0.0084***	0.0065***
	(0.00062)	(0.00060)	(0.00041)	(0.00044)
Constant	-0.21***	-0.11***	-0.0064	-0.052***
	(0.014)	(0.019)	(0.0079)	(0.012)
Observations	15370	15370	15370	15370
R^2	0.266	0.662	0.237	0.633
County FEs		X		X

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

A Appendix

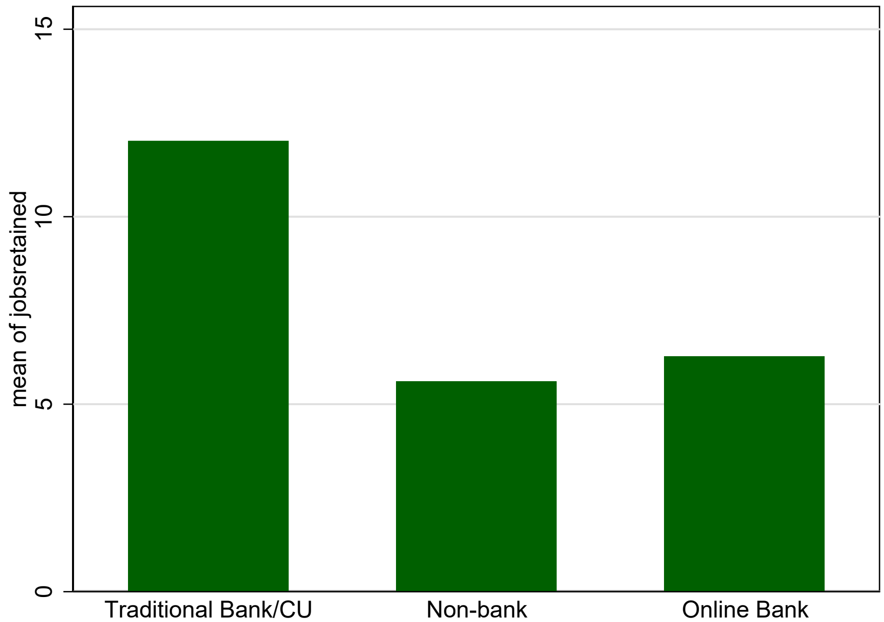


Figure 6: Average PPP Jobs by Institution Type.

Table A1: Bank Branch Density and Fraction of Online/Nonbank Loans, Loan Level Estimates

	(1) Nonbank PPP Loan	(2) Nonbank PPP Loan	(3) Online PPP Loan	(4) Online PPP Loan	(5) Trad. Bk PPP Loan	(6) Trad. Bk PPP Loan
Log Bk Branches	-0.0084***	-0.0073***	-0.0071***	-0.0066***	0.016***	0.014***
	(0.00049)	(0.00046)	(0.00059)	(0.00051)	(0.00095)	(0.00082)
Frac White	-0.073***	-0.065***	-0.057***	-0.047***	0.13***	0.11***
	(0.0028)	(0.0026)	(0.0033)	(0.0027)	(0.0055)	(0.0046)
Frac Commute 45+m	0.050***	0.047***	0.039***	0.031***	-0.089***	-0.078***
	(0.0051)	(0.0049)	(0.0077)	(0.0069)	(0.011)	(0.0099)
Log Pop	0.0080***	0.0061***	0.011***	0.0076***	-0.019***	-0.014***
	(0.00043)	(0.00040)	(0.00050)	(0.00044)	(0.00076)	(0.00067)
Log Est Size	-0.0083***	-0.0065***	-0.010***	-0.0057***	0.019***	0.012***
	(0.00073)	(0.00068)	(0.00093)	(0.00082)	(0.0014)	(0.0012)
Constant	0.066***	0.072***	0.085***	0.095***	0.85***	0.83***
	(0.0047)	(0.0045)	(0.0057)	(0.0050)	(0.0088)	(0.0076)
Observations	4168489	4041610	4168489	4041610	4168489	4041610
R^2	0.026	0.086	0.034	0.104	0.052	0.134
County FEs	X	X	X	X	X	X
NAICS FEs		X		X		X

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

Table A2: PPP Lending and COVID-19 Case Rate

	(1) Nonbank PPP Fraction	(2) Nonbank PPP Fraction	(3) Online PPP Fraction	(4) Online PPP Fraction
Avg Case Rate	0.33***		0.49***	
	(0.054)		(0.089)	
Log Branches		-0.016***		-0.0087***
		(0.0022)		(0.0023)
Avg Case Rate × Log Branches		-0.081**		-0.069
		(0.033)		(0.048)
Constant	0.049***	0.069***	0.098***	0.11***
	(0.0019)	(0.0018)	(0.0039)	(0.0020)
Observations	34813	34813	34813	34813
R^2	0.075	0.568	0.067	0.635
County FEs		X		X

ZIP code level specifications showing the relationship between the share of online/nonbank PPP lending and ZIP code level statistics interacted with the average COVID-19 case rate in March. Robust standard errors. Estimates are weighted by PPP loans per ZIP code. Data calculated from the FDIC Summary of Deposits database and SBA PPP loan data.

Table A3: Predicted Bank Lending and the Economic Shock

	(1) Average Case Rate	(2) Average Case Rate	(3) Unemployment Growth	(4) Unemployment Growth
Predicted PPP	-0.00051	-0.00078	-0.0035	0.012
	(0.00056)	(0.00059)	(0.041)	(0.041)
Bk Branches		0.00066***		-0.042**
		(0.00024)		(0.019)
Constant	0.018***	0.017***	3.36***	3.40***
	(0.0021)	(0.0021)	(0.15)	(0.15)
Observations	15800	15800	7768	7768
R^2	0.875	0.875	0.844	0.844
Commuting Zone FEs		X		X

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

Table A4: PPP Lending and Bank's Own Branch Locations

	(1)	(2)	(3)
	Log PPP Loans	Log PPP Loans	Log PPP Loans
Bk Branches	2.09***	1.83***	1.96***
	(0.075)	(0.11)	(0.046)
Constant	1.37***	1.66***	1.47***
	(0.093)	(0.10)	(0.037)
Observations	52529	46860	52389
R^2	0.146	0.409	0.430
Bank FEs			X
Zip FEs		X	

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

Table A5: Effect of Predicted Bank Lending on Overall Lending

	(1)	(2)	(3)	(4)	(5)	(6)
	Log PPP Loans	Log PPP Loans	Log PPP Loans	Log PPP Loans	Log PPP Loans	Log PPP Loans
Bk Branches	0.89***	0.76***	0.89***	0.76***	0.89***	0.76***
	(0.011)	(0.0094)	(0.011)	(0.0095)	(0.011)	(0.0095)
Predicted Loans (Winsor 90)	0.66***	0.12***				
	(0.026)	(0.029)				
Predicted Loans (Winsor 95)			0.52***	0.094***		
			(0.023)	(0.024)		
Predicted Loans (No Winsor)					0.38***	0.058***
					(0.021)	(0.018)
Constant	1.76***	4.03***	2.26***	4.14***	2.81***	4.28***
	(0.096)	(0.11)	(0.086)	(0.091)	(0.081)	(0.069)
Observations	15930	15930	15930	15930	15930	15930
R^2	0.564	0.800	0.561	0.800	0.553	0.800
County FEs		X		X		X

ZIP code-by-bank level specifications showing the relationship between the predicted number of bank PPP loans, and the total overall number of PPP loans. Robust standard errors. Estimates are weighted by PPP loans per ZIP code. Data calculated from the FDIC Summary of Deposits database and SBA PPP loan data.