Bank Relationships and the Geography of PPP Lending*

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Abstract

I use geocoded data on Paycheck Protection Program (PPP) loans to investigate the spatial distribution of PPP originations. I document three findings. First, half of bank loans come from banks with branches within 2 miles of the borrower. Second, borrowers using a nearby bank get credit sooner, particularly if the bank is a more active PPP lender. Third, census tracts where nearby banks are less active in PPP receive funding later and receive less funding overall, though increased lending from Fintechs offset some of the decline in credit from local banks. The results highlight that despite PPP loan guarantees ameliorating effects of information asymmetries, there were still frictions in substituting away from relationship lenders.

*The analysis and conclusions in this paper are those of the author and should not be interpreted as reflecting the views of the Board of Governors or the Federal Reserve System.

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1 Introduction

As part of the CARES Act, the Paycheck Protection Program (PPP) provided small businesses with over $500 billion in forgivable loans during the early stages of the COVID-19 pandemic. The size and speed of the rollout were unprecedented; most of the credit was extended during the first month of the program despite numerous hurdles, including last-minute policy changes, operational difficulties related to the effects of the pandemic, and the rapid exhaustion of the initial funding allocation.

In this paper, I use geocoded data on the locations of bank branches and PPP borrowers to study in detail the spatial distribution of PPP loan originations. Due to the speed with which the PPP was rolled out, banks reportedly focused on providing credit to existing customers, for whom less due diligence is required before lending. As the majority of banks' small business lending is concentrated within a short distance of their branches, this focus on preexisting relationships caused PPP lending to predominantly fall within banks' branch footprints. Studying the location of PPP lending—and what happens when credit is less available from local lenders—is thus informative as to role bank relationships played in supporting lending.

I present three primary findings. First, the majority of PPP loans are made by banks with a branch in close proximity to the borrower. About half of bank loans come from banks with branches within 2 miles of the borrower and about 30 percent of loans are from banks within a mile. This result highlights the importance of relationships in the provision of PPP loans. PPP loans are fully guaranteed by the US government, removing many of the information-based advantages local banks have in lending. Additionally, restrictions to on-site activities due to the pandemic limited the direct benefit of having nearby physical bank branches. That lending still was strongly tied to bank branch networks indicates that a large share of borrowers received credit through existing bank relationships.

Second, borrowers who got a PPP loan from a nearby lender received credit earlier than other borrowers, consistent with anecdotal reports of banks prioritizing preexisting relationships. The benefits of proximity are particularly pronounced for borrowers from banks that were more active PPP lenders. These banks predominantly served nearby borrowers early in the program before moving on to other borrowers at later stages. Banks with more modest participation concentrated their lending around branches for the entirety of the program, suggesting these banks did not expand beyond serving existing clients.

Third, census tracts near more active banks received more PPP credit and faced smaller delays in receiving loans. In tracts where PPP loans were less available from local lenders, Fintech lenders took on a higher market share, consistent with Erel and Liebersohn (2020). Tracts with a higher share of minority employment similarly faced longer delays in receiving PPP loans and were more likely to be served by Fintech lenders. As minority-owned firms are less likely to have banking relationships (Mills and Battisto, 2020), this result is also consistent with Fintech lenders originating loans where relationship credit was less available. These tract level results hold after accounting for county fixed-effects, indicating that the delays reflect differences in the availability of credit from likely relationship lenders, rather than the availability of credit in the market in general.

Finally, I provide evidence that these effects on tract PPP outcomes are indeed highly localized. While the availability of PPP credit from banks within 2 miles affects origination timing and PPP loan volumes, effects either go away or weaken at greater distances. Most notably, the PPP involvement of banks within 2 miles of a tract affects loan volumes, while the involvement of banks between 2 and 4 miles away does not. Given that PPP lending does not involve collateral monitoring, credit risk, or frequent face-to-face interactions, there is little reason for distance in and of itself to be so meaningful. Consequently, the localized effects likely reflect preexisting relationships, rather than actual difficulties borrowing from further-off banks.

Taken together, these findings highlight the importance of bank relationships in receiving PPP loans. Most borrowers got credit from nearby banks, suggesting they borrowed from banks with whom they had an existing relationship. Tracts received less credit and faced longer delays when local lenders were less active in the program, pointing towards frictions in substituting away from relationship lenders. These results demonstrate an important cost to intermediating aid through the bank sector. While banks were able to distribute funds rapidly, they did so by prioritizing existing clients, thus disadvantaging firms with weaker banking ties. As such firms may have fewer alternatives for offsetting revenue shortfalls—for example credit line draws—frictions in accessing PPP loans were likely highest for the firms most in need of aid.

1.1 Background and Related Literature

The COVID-19 pandemic caused an unprecedented increase in unemployment and temporary business closures starting in March of 2020 (Bartik et al., 2020). In response, Congress passed the Coronavirus Aid, Relief and Economic Security (CARES) Act on March 27th, a $2.2 trillion stimulus bill. One of the the largest components of the bill was the Paycheck Protection Program, which provided low-interest loans to businesses with 500 or fewer employees. Firms were able to request credit for up to 2.5 times monthly payroll, up to a maximum value of $10 million. Loans are forgivable so long as the business maintains employment levels and payrolls.

The program launched on April 3rd, a mere week after the signing of the CARES act. The grant-like nature of the program resulted in very high demand, causing the initial $349 billion allocated to the program to be depleted by April 16th. An additional $320 billion in funding was provided, enabling the PPP to begin taking applications again on April 27th. After another rapid period of origination activity in the following week, the pace of originations slowed. The program stopped taking applications on August 8th, at which time the program had disbursed $525 billion in credit from 5,460 different lenders.[1]

The size of the program and the speed with which it was rolled out caused difficulties upon the initial launch. Final guidance on the program wasn't released until 12 hours before

[1]The PPP reopened on January 11, 2021 after a third round of funding was provided. However, this paper focuses on lending done in the first two rounds.

PPP went live, and "know your customer" requirements hindered the onboarding of new clients (Merker et al., 2020). At the same time, many banks were contending with the effects of branch closures or the shift to work-from-home, causing further operational complications.

Against this backdrop, banks reportedly prioritized their own clients in extending PPP loans. For these borrowers, less additional due diligence was needed to originate a loan. Furthermore, prioritizing existing clients reduced the risk of alienating clients and losing valuable relationships (Joaquim and Netto, 2020). However, banks' chosen allocation of credit may have had undesirable effects, as credit flowed to many borrowers less in need of aid, possibly at the expense of borrowers with weaker banking ties. Indeed, the early rush of PPP lending disproportionately went to less distressed firms (Bartik et al., 2020) and areas less affected by the pandemic (Granja et al., 2020).

While bank relationships appear to be important in receiving PPP credit, studying this topic is complicated by data limitations. Little information is available about lending relationships for the small, private firms that account for the vast majority of PPP loans. To overcome this difficulty, some papers either use data from surveys (Bartik et al., 2020) or public firms (Amiram and Rabetti, 2020; Duchin et al., 2021) to analyze subsets of PPP borrowers for which information on relationships are available.[2] Other papers use county or ZIP code bank branch locations to proxy for relationships, allowing authors to study the full universe of PPP lending, at the cost of using less direct relationship measures (Granja et al., 2020; Erel and Liebersohn, 2020; Li and Strahan, 2020).[3]

I add to this literature by studying the effects of bank PPP involvement at a fine spatial scale. Proxying for preexisting relationships based on branch proximity allows me to analyze the full universe of PPP lending, instead of relying on a small subsample of loans for which relationships are observable. The fine spatial scale also allows me to more narrowly identify

[2]Bartik et al. (2020) use survey data to show that banks are more likely to approve loans to relationship borrowers. Amiram and Rabetti (2020); Duchin et al. (2021) use data from public firms in the PPP to document that relationship borrowers are more likely to get credit and get credit faster.

[3]Erel and Liebersohn (2020) show that Fintech lenders have a higher market share in ZIP codes with fewer branches or a larger minority share of the population, while Li and Strahan (2020) show that banks allocate more PPP loans to counties where they did more small business lending before COVID.

probable relationship lender than other papers that analyze geographic differences in supply conditions. Namely, I analyze credit supply at the tract level, accounting for any county level omitted variables affecting the provision of PPP credit.

2 Data and Summary Statistics

2.1 Data Sources

PPP loan data Loan level data on PPP originations are provided by the Small Business Administration (SBA). For each loan, the data include the name of the lender, various borrower characteristics (address, NAICS code, number of jobs reported) and various loan characteristics (loan amount, origination date). To analyze the geography of originations, I use a geocoded version from geocod.io which contains the latitude and longitude of the borrower addresses in the SBA data.[4]

Distance to lending bank I combine the data on borrower locations with data on bank branch locations from the FDIC's Summary of Deposits (SOD). The SOD includes the latitude and longitude of US bank branches as well as branch-level deposits as of June 2020.

A key object of interest in the loan level data is the distance between the borrower and lender. I use the following process to calculate this distance. First, since the PPP data do not include a lender identifier besides the lender name, I conduct a fuzzy-name match between lender names in the PPP data and the National Information Center's (NIC) Institution Directory. Once I have the lender identifier from NIC, I match PPP loans to the branch locations of the lending bank and find the closest branch to the borrower.[5]

Bank level supply measures In order to analyze how bank conditions affect the availability of credit, I construct two measures of bank credit supply. First, I use an indicator

[4]As of writing, this data is available here: https://www.geocod.io/geocoded-ppp-loan-data/.

[5]Distance is calculated using the haversine formula. Some lender names in the PPP data can match to multiple banks. In these cases, I match the borrower to the bank with the nearest branch.

for whether the lender is one of the top 4 U.S. banks by assets (JPMorgan Chase, Citibank, Wells Fargo or Bank of America). These banks were less likely to approve PPP applications early in the program (Bartik et al., 2020) and generally did less PPP lending relative to their overall small business lending than other banks (Granja et al., 2020).

Second, I construct a bank level supply measure based on the amount of PPP lending relative to assets. I measure the PPP intensity at a bank as the ratio of the total value of 2020 PPP originations to total bank assets from the 2019:Q4 Call Reports. I cap this variable at 0.25 to reduce the influence of a couple of small banks with disproportionately large PPP origination activity:[6]

$$\text{PPP Intensity}_b = \min\{\frac{PPP_b}{Assets_{b,19:Q4}}, 0.25\}$$

Tract level data For tract level analysis, I aggregate the bank level supply measures to compute the average characteristics of banks within 2 miles of each census tract. Using the geocoded branch locations and the locations of tract centroids from 2010 Census Gazetteer files, I find the set of bank branches located within 2 miles of a tract centroid. The two tract level bank supply measures considered are the averages of the top 4 bank indicator and the PPP intensity measure for nearby branches, weighting by the deposits in those branches. As small business lending pre-COVID was highly local, these variables should provide a measure of the likely availability of credit from relationship lenders in an area.

Data on tract level labor market characteristics come from the Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES) Workplace Area Characteristics. LODES provides data on employment for 2010 census blocks by linking state unemployment insurance wage records with administrative and survey data. I use the data on private jobs in 2017, as this is the most recent year that reports employment

[6]There is an economic reason to cap the variable as such. The goal of the PPP intensity measure is to assess the value of a relationship with an active PPP lender. Beyond a certain threshold of PPP lending to assets, lending is likely going to non-relationship borrowers. Consequently, the benefit of a relationship with a bank should be concave in its ratio of PPP lending to assets.

disaggregated by firm size.[7] I aggregate LODES to the census tract level. The key variable of interest is total employment in firms with 500 or fewer employees, generally reflecting employment in PPP-eligible firms.

I also use the LODES data to construct variables reflecting the earnings for employees within the tract. These variables include the share of jobs in the tract earning $1250 or less per month, the share of jobs earning over $3333 per month, and the share of jobs for workers with at least a bachelor's degree. Since PPP loan sizes are pinned to monthly payroll, these variables along with the number of employees in PPP-eligible firms are important controls in specifications predicting PPP lending. Additionally, I use the LODES data to measure the share of employees in a tract that are nonwhite. As minority-owned businesses are less likely to have bank relationships, areas with a high share of minority employment may experience greater frictions in accessing PPP credit.

Finally, pre-COVID small business lending comes from Community Reinvestment Act (CRA) disclosure data. CRA includes information on the volume of loans to firms with less than $1 million in revenue by census tract. I use data from 2019 in order to reflect pre-COVID small business lending relationships. The data is only reported by banks with at least $1.3 billion in assets, and thus does not reflect the extent of small business lending relationships with the smallest banks.

2.2 Summary Statistics

Table 1 presents summary statistics of the main variables of interest, with loan level statistics in Panel 1 and tract level statistics in Panel 2.

The loan level data show that most lending is local, with about half of bank loans coming from lenders with a branch within 2 miles. However, there is a mean distance of 170 miles, reflecting a non-negligible share of loans being made independent of geography.

Regarding the supply measures, the median PPP intensity of the lending bank was about

[7] Alaska is missing for 2017, so I instead use 2016 data there.

5.7% of assets. This number varies notably across loans, with an intensity of 2.7% at the 25th percentile and 10.6% at the 75th percentile.

While a significant share of lending occurred in the early weeks of the program, this was due in part to larger loan sizes during that time. The median bank borrower had to wait 26 days after the start of the program to receive credit and only about 31% of borrowers got loans before the first round of funding ran out.

Table 1: Summary Statistics

Variable	Description	Mean	sd	Percentile 25	50	75	N
Panel 1: Loan level Statistics							
$\text{Distance}_{i,b}$	Miles to nearest branch of lending bank	170.266	503.342	0.799	2.022	8.235	4,563,891
$\text{Local Branch}_{i,b}$	1 if $\text{Distance}_{i,b}$ <2 miles	0.497	0.500	0.000	0.000	1.000	4,563,891
PPP Intensity_b	$\min\{PPP/Assets_{19:Q4}, 0.25\}$	0.083	0.079	0.027	0.057	0.106	4,564,266
Top 4_b	1 if lender is JPM, WFC, C or BAC	0.186	0.389	0.000	0.000	0.000	4,564,266
$\text{ln(Loan Amount)}_{i,b}$	Logarithm of PPP loan balance	10.311	1.465	9.333	10.127	11.225	4,564,265
$\text{Days to Origination}_{i,b}$	Days between origination date and April 3rd	29.402	25.701	11.000	26.000	28.000	4,564,266
$\text{Round 1 Indicator}_{i,b}$	1 if originated by April 16th	0.313	0.464	0.000	0.000	1.000	4,564,266
Panel 2: Tract level Statistics							
PPP Intensity_j	Average PPP intensity of local branches	0.040	0.025	0.022	0.035	0.051	54,434
Top 4 Share_j	Top 4 deposit share within 2 miles	0.336	0.300	0.000	0.297	0.557	54,434
$\text{Days to Origination}_j$	Average days between origination date and April 3	35.596	12.507	27.069	33.460	41.507	54,040
Round 1 Share_j	Share of loans originated by April 16	0.262	0.169	0.128	0.239	0.378	54,040
Fintech Share_j	Share of loans made by Fintech Lenders	0.157	0.136	0.063	0.125	0.209	54,040
Total PPP_j	Logarithm of PPP lending in tract	15.073	1.355	14.261	15.155	15.966	54,040
Local PPP_j	Logarithm of PPP lending by banks within 2 miles	14.158	1.633	13.198	14.310	15.280	53,254
Fintech PPP_j	Logarithm of PPP lending by Fintechs	11.743	1.484	10.825	11.837	12.748	50,739
Round 1 PPP_j	Logarithm of PPP lending in first round	14.310	1.717	13.314	14.526	15.504	51,778
Nonwhite_j	Nonwhite share of employment	0.242	0.166	0.122	0.205	0.319	53,756
ln(SB Emp)_j	Logarithm of small business employment	6.253	1.138	5.576	6.323	7.008	53,739
ln(SB Lending)_j	Logarithm of 2019 small business Lending	6.519	1.275	5.796	6.686	7.402	50,215
ln(Branches)_j	Logarithm of branches within 2 miles	2.077	1.065	1.386	2.197	2.708	54,434
$\text{Earnings} > \$3333_j$	Share jobs earning > $3333 month	0.324	0.149	0.216	0.301	0.412	53,756
$\text{Earnings} < \$1250_j$	Share jobs earning < $1250 month	0.301	0.115	0.220	0.296	0.373	53,756
College_j	Share workers w. college degree	0.186	0.070	0.137	0.174	0.223	53,756

3 Bank Distance and PPP Origination Timing

This section starts by demonstrating graphically that bank PPP lending is concentrated in nearby banks and that originations occur later when nearby lenders are less active in PPP. It then presents regressions analyzing how proximity to the lending bank relates to the speed with which borrowers receive PPP loans.

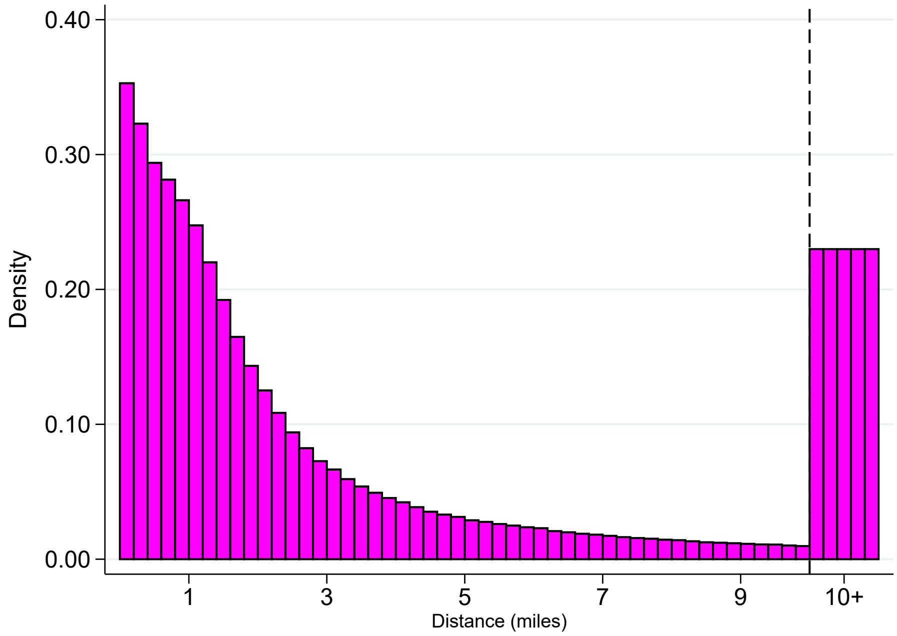
3.1 Graphical Evidence

Figure 1 plots a histogram of the distance between PPP borrowers and the nearest branch of the lending bank. The density falls rapidly as distance rises and starts to level off at around two or three miles. About half of loans are from banks within 2 miles of the borrower. However, there is a long right tail, with about 23% of loans being made by banks that do not have a branch within 10 miles. 39% of these distant loans were provided by three banks—Celtic Bank, Cross River Bank and WebBank—all of whom utilized Fintech partnerships to provide loans. Overall, PPP loans have a similar spatial distribution to pre-COVID small business lending, with a bit more mass in the right tail driven by these online lenders.[8]

That PPP lending remained highly local is interesting as many of the advantages of being a local lender do not apply to PPP loans. Normally, lending is hypothesized as being local because proximity either provides an information advantage in evaluating loans (Agarwal and Hauswald, 2010) or reduces transportation costs involved in originating/monitoring loans (Degryse and Ongena, 2005). PPP loans are fully guaranteed by the U.S. government, removing advantages related to local information or monitoring. Likewise, restrictions on branch operations due to the pandemic weakened the benefit of easy physical access to a bank branch. That PPP lending remained strongly tied to banks' branches despite the advantages of proximity evaporating indicates that relationship lending drove PPP originations. That is, banks continued to lend locally because that is where existing clients were, even though

[8] Brevoort and Wolken (2009) document that the median distance between small firms and the bank servicing them is about 3 miles, with nearly 90% of the lenders being within 30 miles.

Figure 1: Distribution of Lender Distances



Notes: This figure plots a histogram of the distance between a PPP borrower and the address of the nearest branch of the lending bank. The area to the right of the dotted line gives the mass of loans made by lenders more than 10 miles away.

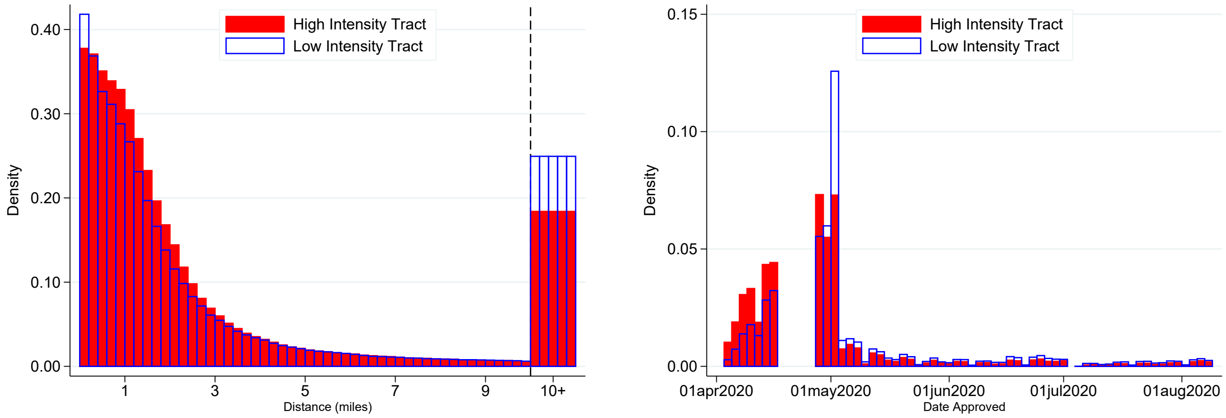
the reasons for favoring nearby firms were no longer relevant.

Figure 2 investigates how the distribution of lender distances and origination timing shifts depending on how active nearby lenders were in the program. Borrowers whose addresses are in "high intensity tracts"—tracts where the deposit weighted PPP intensity of branches within 2 miles exceeds 3 percent—are shown in red, and those in "low intensity tracts" are shown in blue.

The left chart, which displays histograms of lender distances by local PPP intensity, indicates that lending shifts to distant banks when credit is less available from nearby ones. In high intensity tracts, 59 percent of PPP loans are made by banks with branches within 2 miles, compared to only 54 percent for low intensity tracts. This lower mass in low intensity tracts shifts to banks that are more than 10 miles away; distant banks account for 25 percent of lending in low intensity tracts, compared to only 18 percent in high intensity tracts.

This chart suggests two key facts. First, variation in PPP intensity reflects differences

Figure 2: Differences by PPP Intensity of Local Banks



(a) Distribution of Distances

(b) Distribution of Approval Dates

Notes: The left chart plots a histogram of the distance between a PPP borrower and the address of the nearest branch of the lending bank. The area to the right of the dotted line gives the mass of loans made by lenders more than 10 miles away. The right chart plots a histogram of the date a loan was approved. Each histogram divides borrowers into two categories: those in tracts with a deposit weighted PPP intensity of branches within 2 miles exceeding 3 percent (red bars) and those with an average local PPP intensity under 3 percent (hollow blue bars).

in supply. If banks in an area did little PPP lending due to low demand, there would be no reason for this to affect the spatial distribution of lending. If anything, low local demand should reduce the need for distant banks, as local ones would be less bound by capacity constraints. That lending in low intensity areas shifted to distant banks is more consistent with diminished credit availability from nearby banks. Second, out-of-market banks appear to be the outside option when credit is less available from nearby lenders. This justifies the claim that PPP lending is highly localized because of preexisting relationships. If borrowers chose local lenders in PPP for reasons besides preexisting relationships, we'd expect them to shift to slightly further-off lenders when the nearby ones are less active. Instead we see them shift to lenders more than 10 miles away (in actuality the change in the distribution is predominantly to lenders that are over 100 miles away). This pattern is more consistent with borrowers utilizing nearby relationship banks when possible, but turning to distant banks that were willing to serve new clients otherwise.

The right chart, which displays a histogram of origination dates by local PPP intensity, suggests that local supply conditions affect when borrowers received credit. Borrowers in tracts where nearby branches were more active in PPP were more likely to receive credit before funding was exhausted in mid-April. Most borrowers in high intensity tracts ultimately were able to receive approval by the end of April, whereas most borrowers in other tracts had to wait until May or later.

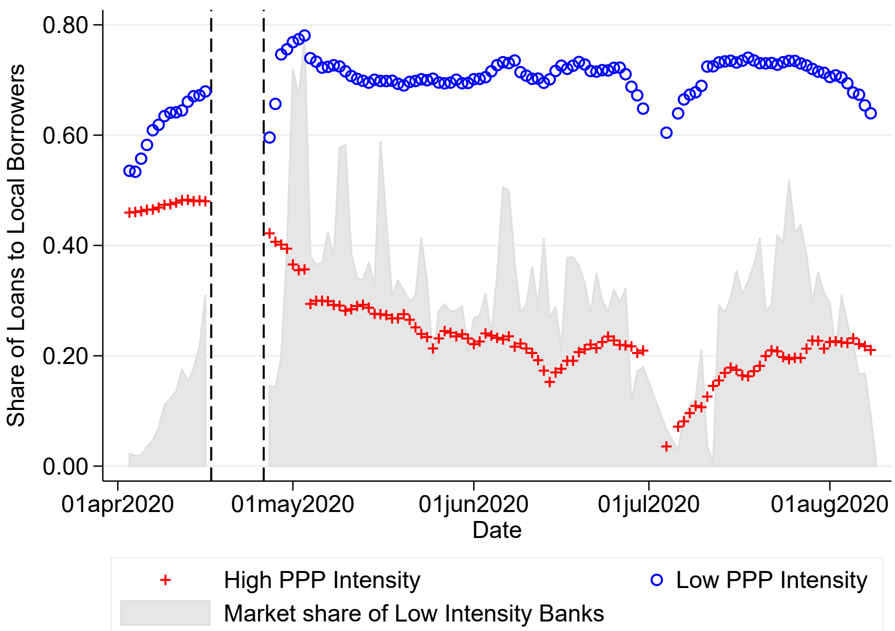
Finally, Figure 3 plots the share of loans made to local borrowers by bank PPP intensity (defined by whether or not PPP originations reach 3 percent of pre-COVID assets), as well as the market share of the low intensity banks, over time. Banks that were less active in PPP (in blue) predominantly served nearby clients throughout the program, with the share of loans to borrowers within 2 miles typically staying in the 60 to 80 percent range. However, these banks were comparatively slower to extend credit; their market share remained below 20 percent for most of the first funding round, and picked-up later. Lending by high intensity banks (in red) started out being fairly localized, with about half of loans going to nearby borrowers, however this local share dropped in the early stages of the second round and typically remained around 25 percent during the later stages of the program.[9]

Overall this figure paints a similar picture to Figure 2, just based on the PPP intensity of the lending bank instead of local banks. Namely, existing clients of major PPP lenders receive credit earlier, as evidenced by the high market share and the focus on nearby borrowers early in the program. Those borrowing from less active banks faced delays, as evidenced by the low market share of such banks in the first round. Finally, those borrowing from non-relationship banks faced delays, as evidenced by the higher rates of non-local lending later in the program.

While this set of findings is suggestive of there being a cost to being reliant on a bank that was less active in PPP, several questions remain: Are the patterns depicted in these figures robust to controlling for other borrower or location-specific differences? How easily

[9] This decline in the share of local lending is mostly driven by changes in the composition of who is lending over time. Namely, some high intensity lenders focused on nearby borrowers and did a lot of lending early in the program, while others, who did more distant lending, were more active late in the program. Within bank, there is still a decline in the local share of lending, as would occur when banks serve existing clients first, and then expand to other borrowers, but it is comparatively modest. More important is the increase in the share of lending provided by internet banks later in the program (Erel and Liebersohn, 2020).

Figure 3: Share of Local Lending over Time



Notes: This figure shows the share of loans by date that are made by banks with branches within 2 miles of the borrower. Red crosses plot results for banks where PPP lending exceeded 3% of pre-COVID assets, and blue circles show shares for low intensity banks. The grey area shows the share of loans made by low intensity banks. All of these shares come from pooling data for loans originated within 2 days of the date listed on the x-axis. This pooling reduces noise, for example, due to low volumes during weekends.

can borrowers substitute between lenders? Do supply differences affect loan volumes, or just timing? I investigate these questions in the remainder of the paper.

3.2 Loan level origination timing

Table 2 presents the results of regressing the number of days until a PPP loan is originated on an indicator for whether the loan is from a bank with a branch within 2 miles and measures of how active the lending bank was in the PPP. All specifications control for the size of the loan (the natural logarithm of the loan amount) and include county and 3-digit industry fixed effects.

In column 1, the extent of PPP involvement of the lending bank is measured by an indicator for whether the bank is one of the top four banks by assets, as these institutions were less active in the PPP (Granja et al., 2020; Bartik et al., 2020). The results show that clients of the four largest banks need to wait over 3 days longer on average to get their PPP loans compared to borrowers from other banks. There is also a benefit to proximity, as borrowers from banks with nearby branches get their loans almost 5 days before those borrowing from a distant bank.

Column 2 adds in the PPP intensity (PPP lending to assets) of the lending bank to the specification. The results show that borrowers from more active lenders on average received credit later. This result does not mean that high PPP intensity lenders were slower to extend credit. Instead, the result likely indicates that the most active lenders originated more loans late in the program to non-relationship borrowers. The coefficient on the local branch indicator falls by over half when PPP intensity is included, indicating that the benefits of proximity partly reflect borrowers not needing to turn to one of the non-local lenders that did much of the lending late in the program.

To understand the likely effect of *having a relationship* with an active PPP lender, the results in column 3 interact PPP intensity and the top 4 bank indicator with the indicator for whether the borrower is close to the lending bank. The coefficient on PPP intensity changes signs for nearby banks. Borrowers from a bank with a 5 percentage point higher PPP intensity receive credit about 1.8 days sooner if that bank is within 2 miles, but 3.5 days later if the bank is further off. This finding suggests that there is a benefit to having a relationship with a more active PPP lender. However, these high-intensity lenders also appear to have done more non-relationship lending later in the program. The difference in origination speed for local and non-local borrowers is less stark for the top 4 banks; being close to the bank mitigates, but does not do away with, the delay from borrowing from a top 4 bank.[10]

The results in the last three columns—where an indicator for whether a loan is originated in the first round of the program is the dependent variable—tell a similar story. Column 4 shows that loans from a top 4 bank are about 25 percentage points less likely to occur in the first round of PPP, and loans from a nearby bank are 5 percentage points more likely to occur in the first round. Column 5 shows that a 5 percentage point increase in PPP intensity is associated with a 1.6 percentage point reduction in the likelihood a loan occurs in the first round. The last column shows that this delay is driven by distant lending; a 5 percentage point increase in PPP intensity raises the likelihood of getting credit in the first round by about 6 percentage points for nearby borrowers, but reduces it by over 3 percentage points for distant borrowers.

In short, there is a benefit to being close to a major PPP lender. A higher PPP intensity is associated with a shorter delay in receiving credit for nearby borrowers, suggesting lenders served relationship borrowers first. While borrowing from a top 4 bank resulted in less of a delay for nearby borrowers, it still resulted in a delay, indicating a cost to having a relationship with a top 4 bank.

[10] There are different tiers of relationships that were relevant to when borrowers could borrow. For example, Chase did not initially accept applications from people who only had a business credit card with them but expanded access in July (Zhou, 2020). As business credit card loans are less likely to be local (Adams et al., 2020), such a pattern could contribute to the more severe delays for non-local borrowers of the largest banks.

Table 2: Bank Proximity and Origination Speed

	Days to Origination			Round 1 Indicator×100		
	(1)	(2)	(3)	(4)	(5)	(6)
Top 4_b	3.29**	7.76**	10.27**	-24.57**	-27.29**	-30.81**
	(0.35)	(0.24)	(0.33)	(0.53)	(0.56)	(0.43)
PPP Intensity_b		51.28**	69.91**		-31.20**	-63.55**
		(4.12)	(4.69)		(3.22)	(3.01)
Local $\text{Branch}_{i,b}$	-4.77**	-2.20**	5.85**	5.32**	3.75**	-10.20**
	(0.38)	(0.12)	(0.37)	(0.36)	(0.25)	(0.41)
x Top 4_b			-6.73**			10.63**
			(0.47)			(0.58)
x PPP Intensity_b			-105.27**			184.82**
			(5.56)			(6.01)
ln(Loan $\text{Amount})_{i,b}$	-5.89**	-5.67**	-5.52**	11.24**	11.10**	10.84**
	(0.05)	(0.04)	(0.04)	(0.20)	(0.22)	(0.22)
R^2	0.204	0.218	0.227	0.263	0.265	0.273
Obs.	4,431,446	4,431,446	4,431,446	4,431,446	4,431,446	4,431,446
County FE?	X	X	X	X	X	X
3-Digit NAICS FE?	X	X	X	X	X	X

Notes: This table presents estimates from regressions predicting days until Origination (columns 1–3) or an indicator for whether a loan was originated during the first round of PPP funding (columns 4–6). The round 1 indicator is multiplied by 100, so estimates are in terms of the percentage point change in the probability of being funded in round 1. The primary explanatory variables are an indicator for whether the bank is a top 4 bank, the PPP intensity (PPP to assets) of the lending bank, and an indicator for whether the bank has a branch within 2 miles of the borrower. The specifications in columns 3 & 6 additionally interact the indicator for whether the bank has a local branch with the two supply measures. All specifications control for the size of the loan and include county and 3-digit NAICS fixed effects. Standards errors, in parentheses, are clustered by county. $^{+}$,*,** indicate significance at 10%, 5% and 1%, respectively.

4 Effects of Credit Availability from Nearby Banks

This section analyzes tract level PPP outcomes based on how active nearby banks are in PPP. First, I show that borrowers receive credit sooner if nearby banks are more active, then I show that tracts receive more PPP credit when nearby lenders are more active.

4.1 Tract level origination timing

The results thus far indicate that there is a benefit to having a relationship with a lender that is active in PPP. Borrowers close to (and thus likely to have a relationship with) banks with a high PPP intensity received loans sooner than other borrowers, while non-local borrowers from high-intensity banks and clients of the top 4 banks received credit later than other borrowers. Now I investigate the implications of these differences for when particular areas get credit. If most borrowers who face delays from one bank can easily get credit from another, the costs of having a relationship with a less active lender may be modest. However, if frictions in accessing PPP loans from non-relationship lenders are pronounced, areas near less active lenders may face notable delays in receiving credit.

Table 3 regresses tract level PPP outcomes on the average PPP intensity and top 4 indicator for the branches within 2 miles of a census tract, weighted by branch deposits. Odd columns present OLS estimates of how the PPP participation of local banks affects lending outcomes, while even columns present results weighting by tract small business employment. Most estimates are not sensitive to weighting, so I predominantly discuss the unweighted results unless the two substantively differ.

In the first two columns, the dependent variable is the average days until origination for the PPP loans in a census tract. A 5 percentage point increase in the PPP intensity of local banks reduces the average time to origination by about 0.8 days. Likewise, if all of the branches within 2 miles are from top 4 banks, borrowers in the tract will on average get credit about 1.6 days later.

Table 3: Tract Level Origination Speed

Dep. Variable	Days to Origination		Round 1 Share (pp)		Fintech Share (pp)	
	(1)	(2)	(3)	(4)	(5)	(6)
PPP Intensity$_j$	-15.71**	-13.80**	32.46**	31.85**	-13.89**	-12.45**
	(3.68)	(2.29)	(3.35)	(3.57)	(4.34)	(2.41)
Top 4 Share$_j$	1.60**	1.24**	-1.13**	-1.18**	1.51**	1.22**
	(0.52)	(0.41)	(0.34)	(0.43)	(0.53)	(0.40)
Nonwhite$_j$	24.99**	22.15**	-12.75**	-17.48**	23.56**	19.51**
	(2.34)	(2.18)	(1.34)	(2.08)	(2.99)	(2.75)
ln(SB Emp)$_j$	-3.94**	-3.62**	5.11**	5.69**	-3.07**	-2.75**
	(0.10)	(0.09)	(0.13)	(0.13)	(0.16)	(0.13)
ln(SB Lending)$_j$	-0.38**	0.07	-0.75**	-1.28**	-0.45**	-0.03
	(0.12)	(0.08)	(0.07)	(0.09)	(0.13)	(0.11)
ln(Branches)$_j$	-0.94**	-0.50**	0.48**	0.18$^+$	-0.60**	-0.27*
	(0.15)	(0.08)	(0.08)	(0.10)	(0.17)	(0.12)
R^2	0.643	0.674	0.733	0.798	0.573	0.585
Obs.	49,030	49,030	49,030	49,030	49,030	49,030
County FE?	X	X	X	X	X	X
Employment Weighted?		X		X		X

Notes: This table presents estimates from the equation:

$$y_{j,c} = \alpha_c + \beta \text{PPP Intensity}_j + \psi \text{Top 4 Share}_j + \gamma' X_j + \varepsilon_j$$

where $y_{j,c}$ is a PPP outcome for a tract j in county c. This is the average number of days until origination for the loans in the tract in columns 1 & 2, the percentage of loans originated in the first round in columns 3 & 4, and the percentage of loans made by Fintech lenders in columns 5 & 6. PPP intensity is the ratio of PPP lending to pre-COVID assets for the banks with branches within 2 miles of the tract centroid, weighted by the deposits in those branches, and Top 4 Share is the share of those deposits in one of the four largest U.S. banks. X_j is a vector of tract-level controls, including the share of tract employment that is nonwhite, the logarithms of 2017 small business employment ($\leq$500 employees) and 2019 small business lending in the tract, and the logarithm of the number of branches within 2 miles of the tract. Each specification includes county fixed-effects, and even-numbered specifications weight by 2017 tract small business employment. Standards errors, in parentheses, are clustered by county. $^{+}$,*,** indicate significance at 10%, 5% and 1%, respectively.

The results also show that the racial composition of the workforce relates strongly to the speed with which PPP loans are extended. A one standard deviation increase in the share of employees that are nonwhite (0.17), results in a 4.2 day delay in receiving credit, on average. This result may be indicative of minority-owned firms being less likely to have bank relationships (Mills and Battisto, 2020), resulting in less credit availability controlling for the average PPP intensity of nearby lenders.[11]

Columns 3 and 4 present results with the share of PPP lending occurring during the first round as the dependent variable. Consistent with the aforementioned delays in receiving credit, a 5 percentage point higher PPP intensity increases the share of lending during the first round by 1.6 percentage points. Having all of the nearby branches be from the top 4 banks reduces the round 1 share by about 1.1 percentage points. Finally, a one standard deviation increase in the minority employment share reduces the share of lending in the first round by about 2.1 percentage points.

Consistent with the loan-level results, these findings suggest that there is a benefit in terms of prompt access to PPP financing to having a relationship with a significant PPP lender, and a cost (beyond what is reflected in the coefficient on PPP intensity) to being a client of one of the top 4 banks. However, the delays implied by the tract level results are less than what is reflected in the loan level results, with the coefficients on PPP intensity and the top 4 share declining by over half in tract results compared to the estimates for local borrowers in the loan level results.[12] This may partly be due to local deposit market shares being an imperfect proxy for small business lending market shares. However, this may also reflect the ability of borrowers to switch away from local lenders if they are slower to extend credit. For example, even if the top 4 banks are slow to extend credit, if borrowers are able

[11]While the SBA collected data on the race of borrowers, that field is rarely populated. Consequently it is only feasible to analyze results based on the racial composition of the local workforce instead of the demographics of the owners themselves.

[12]The coefficient on PPP intensity for borrowers within 2 miles (summing the linear and interaction term) was about -35 in loan level results predicting days until origination, compared to an effect of -16 in the tract results averaging the PPP intensity of banks within 2 miles. The coefficients on the top 4 indicator/deposit share were about 3.5 in the loan level results and 1.6 in the tract level results.

to quickly switch to other lenders, this could mitigate the delay in receiving credit.

The results in columns 5 and 6 suggest that Fintech lenders served as a substitute for local banks when local banks were less active in PPP. The dependent variable is the share of PPP loans originated by Fintech lenders.[13] The results show that a 5 percentage point increase in PPP intensity for nearby banks reduces the market share of Fintechs by about 69bp (relative to a mean Fintech share of 16 percent). If all local banks are in the top 4, this raises the Fintech market share by about 1.5 percentage points.

Most of the discussion so far has treated PPP intensity as if it were exogenous. One potential alternative explanation of the results is that the banks with a high PPP intensity are ones that have relationships with clients that are easier to serve. These banks thus service their clients faster and are able to do more lending in general. There are a couple of reasons to think that this is not the case. First, the fact that Fintech lenders do more lending in areas around low-intensity banks indicates that the slower pace of bank lending is due more to local banks' actions than rather than general difficulties lending in a particular area. Second, PPP intensity is an aggregate bank outcome determined by lending throughout their branch network, weakening the tie between PPP lending in a given tract and PPP intensity at the bank level. That said, the top 4 share may be a cleaner measure of the supply of credit from local banks, as the scale of operations of these banks removes the concern that PPP intensity at the bank reflects differences in local conditions. For this reason, Table A1 in the Appendix presents similar estimates but only using the top 4 share to measure local supply conditions. The estimated effect of being near a top 4 bank strengthens a bit, as the effect is no longer partly captured by the PPP intensity variable.

4.2 Tract level origination volumes

While delays in receiving PPP loans may have been harmful, particularly for the most constrained and at-risk firms, the effects of these delays are likely secondary to the damage

[13]The Fintech share is the share of loans made by the following lenders: Celtic Bank, Cross River Bank, Intuit, Fundbox, Kabbage, Readycap and WebBank.

if some firms were shut out from receiving PPP entirely. In Table 4, I assess whether the characteristics of nearby banks affect the total volume of PPP lending that the firms in a tract are able to get.

Recall that the PPP program essentially provided credit for up to 2.5 times monthly payroll for businesses with 500 or fewer employees.[14] This means that the logarithm of total PPP lending in an area will roughly be the sum of: i. ln(Small Business Employment), ii. ln(2.5 $\times$ Average Monthly Payroll of Eligible Firms) and iii. ln(Share of Eligible Payroll Funded). In order to address how local bank characteristics affect the share of eligible payroll funded, I regress the logarithm of PPP lending on the tract level measures of PPP supply conditions, controlling for the logarithm of employment in firms with fewer than 500 employees (to account for i.) and the following variables pertaining to average earnings (to account for ii.): the share of jobs earning under $1250 per month, the share of jobs earning over $3333 per month, and the share of workers with a college degree.

The first two columns present results with the logarithm of total tract PPP lending as the dependent variable. The coefficients on the controls are about as expected. The coefficient on ln(SB Emp) is 0.87 in the unweighted results and 0.94 in the weighted results, not far from the expected value of 1. A greater share of employees with high earning jobs is associated with significantly higher PPP lending, reflecting the higher allowable loan sizes. As these controls seem to reasonably account for differences in wages and small business employment across tracts, the coefficients on the bank supply measures should reflect differences in the propensity of eligible firms to receive loans.

Overall, the results indicate that the effect of local PPP intensity on loan volumes is modest. The coefficient on PPP intensity indicates that a 5 percent increase in PPP intensity for the banks with branches within 2 miles of a tract increases total PPP lending by about 1.8 percent. The estimated effect of having all nearby branches belong to one of the four

[14]These terms are simplifications of somewhat more complex eligibility requirements. For example, payroll costs are limited to $100,000 per employee and loan sizes were capped at $10 million. Passive businesses are ineligible even if they meet the size requirement, while firms in the accommodation and food services industry are eligible so long as they employ fewer than 500 *per location*.

largest banks is to lower PPP lending by about 2 percent, but the result is statistically insignificant and sensitive to whether or not the regression is employment-weighted.

The results pertaining to the racial composition of employees are ambiguous. The weighted results indicate that tracts with more nonwhite employees get significantly less credit, but the OLS results indicate that there is no significant difference. Assessing differences in the ability to get PPP loans is complicated by the racial wage gap: lower PPP lending could reflect lower average earnings among minority employees (reducing loan sizes) or greater frictions in accessing PPP credit (reducing loan counts).[15] In the weighted results, the minority share of the population is significant but the coefficient on the college share is about 0, while in the OLS results we get the reverse. This points towards difficulty statistically distinguishing direct effects of race on origination volumes from indirect effects operating through wages.

While the total amount of PPP funding is only modestly affected by local characteristics, the composition of funding is much more strongly affected. The results in columns 3 and 4 present estimates for how the total lending of banks with branches within 2 miles of the tract differs based on how active those banks are in PPP overall. While local banks having a 5 percentage point higher PPP intensity only increases total PPP lending by less than 2 percent, it increases the PPP lending by local banks by almost 20 percent. Again, there is no significant effect of having a higher share of deposits from top 4 banks (beyond what is reflected in PPP intensity). However, when PPP intensity is excluded from the specification, estimates imply that having the top 4 banks account for all local branches reduces PPP lending by local banks by 15 percent (see Appendix Table A2).

That lending by nearby banks is so much more sensitive to local credit conditions than aggregate lending suggests other lenders enter the market to make up for the weaker activity of nearby lenders. The results in columns 5 and 6 show that a 5 percentage point decrease

[15] I focus on loan volumes due to the availability of tract level data on small business employment and earnings enabling me to approximately control for small business payroll. Lacking granular data on the number of small businesses in a tract, it would be more difficult to tell whether a difference in loan counts was due to differences in the number of small businesses or due to differences in loan supply.

Table 4: Tract Level Origination Volumes

	Total Lending		Local Bank Lending		Fintech Lending		Round 1 Lending	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PPP Intensity$_j$	0.36*	0.42*	3.90**	3.67**	-1.45**	-1.65**	0.87**	1.04**
	(0.18)	(0.17)	(0.33)	(0.40)	(0.37)	(0.40)	(0.27)	(0.22)
Top 4 Share$_j$	-0.02	0.00	0.04	-0.01	0.02	-0.03	-0.14**	-0.08*
	(0.02)	(0.02)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.03)
Nonwhite$_j$	-0.06	-0.40**	-0.61**	-0.83**	1.13**	0.73**	-0.76**	-0.95**
	(0.09)	(0.06)	(0.07)	(0.08)	(0.22)	(0.22)	(0.08)	(0.08)
ln(SB Emp)$_j$	0.87**	0.94**	0.94**	0.97**	0.44**	0.61**	1.12**	1.11**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
ln(SB Lending)$_j$	0.17**	0.16**	0.18**	0.18**	0.25**	0.31**	0.10**	0.12**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ln(Branches)$_j$	0.00	0.00	0.48**	0.43**	-0.02*	-0.01	0.03**	0.02**
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Earnings > \$3333	0.44**	0.40**	0.02	-0.20*	-0.23*	-0.28*	0.88**	0.88**
	(0.08)	(0.06)	(0.11)	(0.10)	(0.11)	(0.13)	(0.11)	(0.09)
Earnings < \$1250	-0.79**	-0.86**	-0.50**	-0.68**	-0.02	0.42**	-0.99**	-1.09**
	(0.09)	(0.07)	(0.10)	(0.10)	(0.15)	(0.15)	(0.12)	(0.10)
College$_j$	0.37**	-0.00	1.29**	1.02**	0.44**	0.43$^+$	-0.03	-0.59**
	(0.11)	(0.13)	(0.15)	(0.17)	(0.17)	(0.22)	(0.15)	(0.15)
R^2	0.819	0.909	0.744	0.843	0.551	0.732	0.720	0.839
Obs.	49,030	49,030	48,401	48,401	46,332	46,332	47,129	47,129
County FE?	X	X	X	X	X	X	X	X
Employment Weighted?		X		X		X		X

Notes: This table presents estimates from the equation:

$$ln(y_{j,c}) = \alpha_c + \beta \text{PPP Intensity}_j + \psi \text{Top 4 Share}_j + \gamma' X_j + \varepsilon_j$$

where $y_{j,c}$ is the volume of a particular type of PPP lending in tract j: total PPP lending in columns 1 & 2, PPP lending by banks with branches within 2 miles of the tract in columns 3 & 4, PPP lending by Fintech firms in columns 5 & 6, and PPP lending in the first funding round in columns 7 & 8. PPP intensity is the ratio of PPP lending to pre-COVID assets for the banks with branches within 2 miles of the tract centroid, weighted by the deposits in those branches, and Top 4 Share is the share of those deposits in one of the four largest U.S. banks. X_j is a vector of tract level controls, including the logarithms of 2017 small business employment ($\leq$500 employees) and 2019 small business lending in the tract; the logarithm of the number of branches within 2 miles of the tract; and the shares of jobs in the tract that earn over \$3333 per month, earn under \$1250 per month, are held by a worker with a college degree or are held by nonwhite employees. Each specification includes county fixed-effects, and even-numbered specifications weight by 2017 tract small business employment. Standards errors, in parentheses, are clustered by county. $^{+}$,*,** indicate significance at 10%, 5% and 1%, respectively.

in PPP intensity among nearby banks increases the lending of Fintech lenders by over 7 percent. Thus, the higher market share of Fintechs in areas around less active banks is not merely due to the weaker lending by local banks. Instead, Fintech lenders increase lending in absolute terms and offset the declines from local banks. Fintech lenders are particularly active in areas with a higher share of minority employment, with a one standard deviation increase in minority employment resulting in a 19 percent increase in tract Fintech lending.

Overall, the results show that when local banks are less active in PPP, Fintech lenders provide more credit. Although low-intensity banks provide less credit to the tract than other banks would, the ultimate effect on PPP provisioning is relatively modest. However, as Fintech lenders were approved as PPP lenders later, and likely lacked some of the benefits a relationship lender would have had, this need to substitute to other lenders still delayed access to credit. The results in the last two columns show that tracts near low-intensity lenders, especially the top 4 lenders, received significantly less credit during the first round. While it seems that firms in these tracts were usually able to get funding eventually, the inability to channel credit to firms in the earliest stage of the PPP—when unemployment was at its peak—may have limited some of the program's effectiveness (Doniger and Kay, 2020).

4.3 Effects of Bank Shocks by Distance

The results so far show that the degree of involvement of the banks within 2 miles of a tract is important in determining the amount of credit provided to a tract and the speed with which it is received. Now I investigate whether this is the appropriate distance to consider, or whether the activity of more distant banks matters as well.

Figure 4 presents estimates of $\{\beta_d\}$ from the equation:

$$y_{j,c} = \alpha_c + \sum_d \left(\beta_d \text{PPP Intensity}(d)_j + \psi_d \text{Top 4 Share}(d)_j\right) + \gamma' X_j + \varepsilon_j$$

where PPP Intensity$(d)_j$ is the deposit weighted average PPP intensity of banks with branches between $d-2$ and d miles from a census tract, and Top 4 Share$(d)_j$ is the share of deposits within that distance band belonging to the top 4 banks. $y_{j,c}$ is one of the previously discussed tract level PPP outcomes: the share of loans originated in the first round (Panel 4a), the average days until origination (Panel 4b), the share of loans to Fintechs (Panel 4c) or the logarithm of PPP originations (Panel 4d).[16]

The top two charts show that it is predominantly the banks within two miles that affect the timing with which PPP loans are received. The effects of PPP intensity on the share of loans originated in the first round and on the average days until origination are roughly twice as large for banks within 2 miles as for banks 2–4 miles away. A higher PPP intensity for banks at higher distances is still associated with earlier access to credit, however, the effects are smaller than for nearby banks and often insignificant.

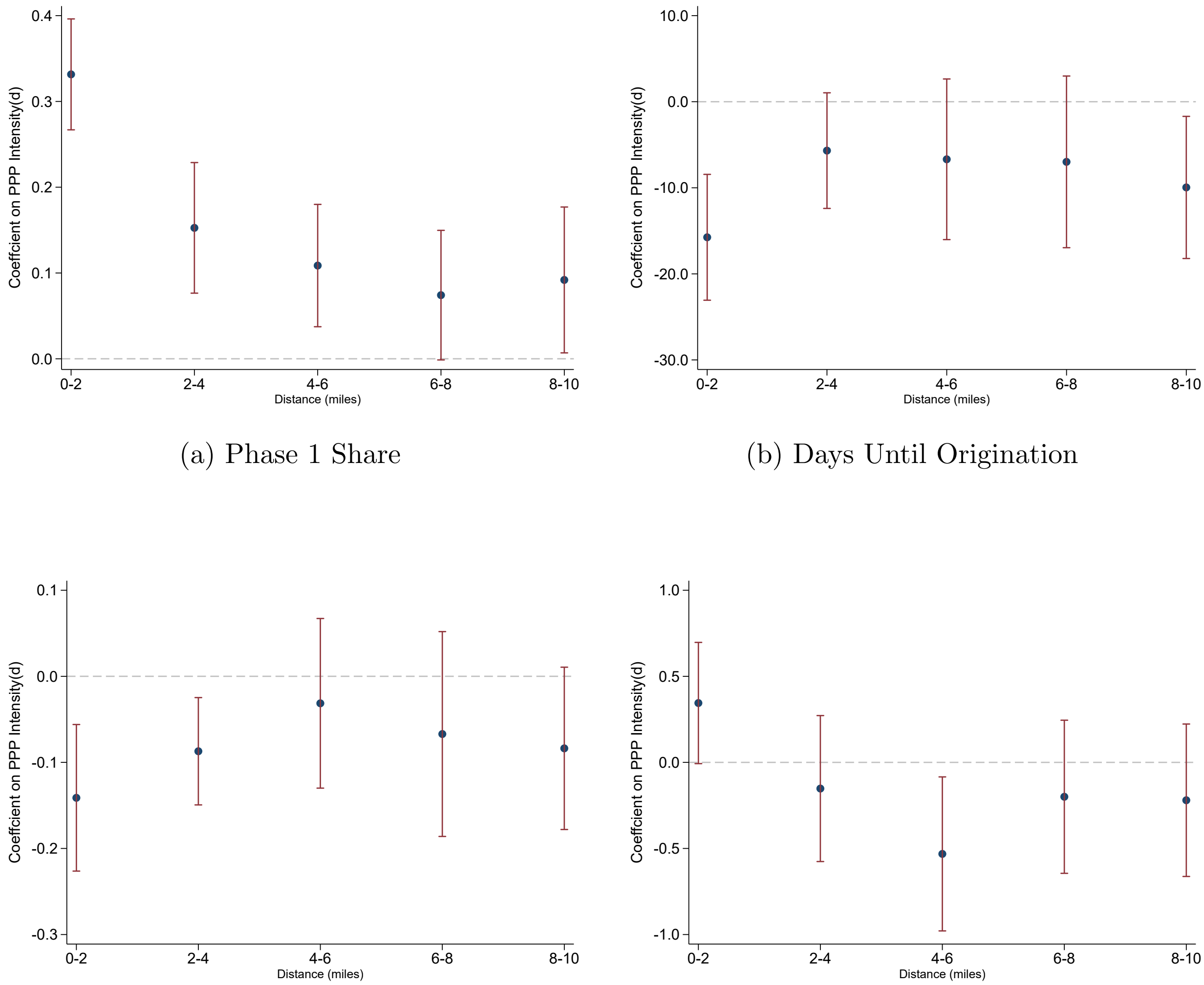
Panel 4c shows that the effects of PPP intensity on the share of loans to Fintechs is similarly very localized. The PPP intensity of banks within 2 miles matters about 50% more than for banks 2–4 miles away, and effects are insignificant beyond 4 miles.

Finally, Panel 4d shows that a higher PPP intensity of banks within 2 miles is associated with higher tract PPP lending, however the relationship between PPP intensity and loan volumes turns negative for higher distances.

Overall, these results show that variation in supply conditions have very localized effects. These effects are unlikely to be driven by bank preferences for nearby borrowers as loan guarantees remove the benefits of local information or easier monitoring. Likewise, these effects are unlikely to be driven by borrower preferences for nearby banks, as transit costs of going to a bank just a few miles away are unlikely to be prohibitive. However, most preexisting small business relationships were with banks within a few miles (Brevoort and Wolken, 2009), thus the narrow geographic scope of supply shocks is consistent with frictions

[16] X_j is as in Table 4, but with an additional dummy variable indicating whether there are no banks within a particular distance band. The two supply measures are recoded to 0 when there are no banks within a band and tracts are dropped if there are no banks within 2 miles so as to maintain the same sample as in the previous analysis.

Figure 4: Effects of PPP Intensity by Bank Distance



(a) Phase 1 Share

(b) Days Until Origination

(c) Fintech Share

(d) ln(PPP Originations)

Notes: This figure plots estimates and 95% confidence intervals for $\{\beta_d\}$ from the specification:

$$y_{j,c} = \alpha_c + \sum_d \left(\beta_d \text{PPP Intensity}(d)_j + \psi_d \text{Top 4 Share}(d)_j\right) + \gamma' X_j + \varepsilon_j$$

where PPP Intensity$(d)_j$ is the deposit weighted average PPP intensity or the share of deposits in top 4 banks for branches between $d-2$ and d miles from a census tract. $y_{j,c}$ is a PPP outcome for tract j: the share of loans approved in the first round in (a), the average number of days between the start of PPP and the approval date in (b), the share of lending by Fintechs in (c), and the natural logarithm of the value of PPP approvals in (d). X_j is a vector of tract-level controls, including the the logarithms of 2017 small business employment ($\leq$500 employees) and 2019 small business lending in the tract; the logarithm of the number of branches within 2 miles of the tract; the shares of jobs in the tract that earn over \$3333 per month, earn under \$1250 per month, are held by a worker with a college degree or are held by nonwhite employees; and dummy variables indicating whether there are no banks within a distance band. Supply measures are recoded as 0 when there are no banks within a band so as to keep a consistent sample with Table 4. Each specification includes county fixed-effects. Standards errors are clustered by county.

in switching from relationship lenders driving the results.

5 Conclusion

I use geocoded data on PPP borrowers and bank branches to study the spatial distribution of PPP originations. I show that about half of bank PPP loans are made by banks with a branch within 2 miles of the borrower. Borrowers are quicker to receive loans if they get credit from a nearby bank, especially if that bank is a more prominent PPP lender. Borrowers in census tracts where nearby banks are less active PPP lenders receive funding later and receive less funding overall, though increased lending from Fintechs offset some of the decline in credit from local banks. These results indicate that bank relationships were important in quickly receiving credit, though less relationship-oriented lenders were able to (eventually) compensate for a lack of available credit from relationship lenders.

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A Appendix

Table A1: Top 4 Banks and Tract Origination Speed

Dep. Variable	Days to Origination		Phase 1 Share (pp)		Fintech Share (pp)	
	(1)	(2)	(3)	(4)	(5)	(6)
Top 4 Share$_j$	2.34**	1.90**	-2.67**	-2.72**	2.17**	1.82**
	(0.42)	(0.38)	(0.29)	(0.40)	(0.43)	(0.39)
Nonwhite$_j$	25.04**	22.27**	-12.85**	-17.75**	23.60**	19.62**
	(2.34)	(2.17)	(1.33)	(2.05)	(2.99)	(2.74)
ln(SB Emp)$_j$	-3.95**	-3.62**	5.12**	5.69**	-3.08**	-2.75**
	(0.10)	(0.09)	(0.13)	(0.13)	(0.16)	(0.13)
ln(SB Lending)$_j$	-0.39**	0.07	-0.75**	-1.27**	-0.46**	-0.04
	(0.12)	(0.09)	(0.07)	(0.09)	(0.13)	(0.11)
ln(Branches)$_j$	-0.94**	-0.50**	0.48**	0.18$^+$	-0.60**	-0.27*
	(0.15)	(0.08)	(0.08)	(0.10)	(0.17)	(0.12)
R^2	0.643	0.673	0.733	0.797	0.572	0.584
Obs.	49,030	49,030	49,030	49,030	49,030	49,030
County FE?	X	X	X	X	X	X
Employment Weighted?		X		X		X

Notes: This table presents estimates from the equation:

$$y_{j,c} = \alpha_c + \psi \text{Top 4 share}_j + \gamma' X_j + \varepsilon_j$$

where $y_{j,c}$ is a PPP outcome for a tract j in county c: the average number of days until origination for the loans in the tract in columns 1 & 2, the percentage of loans originated in the first round in columns 3 & 4, and the percentage of loans made by Fintechs in columns 5 & 6. Top 4 share is the share of deposits in branches within 2 miles of the tract that belong to one of the four largest U.S. banks. X_j is a vector of tract-level controls including the share of tract employment that is nonwhite, the logarithms of 2017 small business employment ($\leq$500 employees) and 2019 small business lending in the tract, and the logarithm of the number of branches within 2 miles of the tract. Each specification includes county fixed-effects, and even-numbered specifications weight by tract small business employment. Standards errors, in parentheses, are clustered by county. $^{+}$,*,** indicate significance at 10%, 5% and 1%, respectively.

Table A2: Top 4 Banks and Tract Origination Volumes

	Total Lending		Local Bank Lending		Fintech Lending		Round 1 Lending	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Top 4 Share$_j$	-0.04*	-0.02	-0.15**	-0.18**	0.09*	0.05	-0.18**	-0.14**
	(0.02)	(0.01)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)
Nonwhite$_j$	-0.06	-0.41**	-0.62**	-0.86**	1.13**	0.74**	-0.76**	-0.96**
	(0.09)	(0.06)	(0.07)	(0.08)	(0.22)	(0.22)	(0.08)	(0.08)
ln(SB Emp)$_j$	0.87**	0.94**	0.94**	0.97**	0.44**	0.61**	1.12**	1.11**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
ln(SB Lending)$_j$	0.17**	0.16**	0.18**	0.18**	0.25**	0.31**	0.10**	0.12**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ln(Branches)$_j$	0.00	0.00	0.47**	0.43**	-0.02*	-0.01	0.03**	0.02**
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Earnings > \$3333	0.44**	0.40**	0.02	-0.22*	-0.23*	-0.27*	0.88**	0.88**
	(0.08)	(0.06)	(0.11)	(0.10)	(0.11)	(0.13)	(0.11)	(0.09)
Earnings < \$1250	-0.79**	-0.87**	-0.50**	-0.69**	-0.02	0.42**	-0.99**	-1.09**
	(0.09)	(0.07)	(0.10)	(0.10)	(0.15)	(0.15)	(0.12)	(0.10)
College$_j$	0.37**	-0.00	1.29**	1.02**	0.43*	0.42$^+$	-0.03	-0.59**
	(0.11)	(0.13)	(0.15)	(0.18)	(0.17)	(0.22)	(0.15)	(0.15)
R^2	0.819	0.909	0.743	0.841	0.551	0.732	0.720	0.839
Obs.	49,030	49,030	48,401	48,401	46,332	46,332	47,129	47,129
County FE?	X	X	X	X	X	X	X	X
Employment Weighted?		X		X		X		X

Notes: This table presents estimates from the equation:

$$ln(y_{j,c}) = \alpha_c + \psi \text{Top 4 share}_j + \gamma' X_j + \varepsilon_j$$

where $y_{j,c}$ is the volume of a particular type of PPP lending in tract j: total PPP lending in columns 1 & 2, PPP lending by banks with branches within 2 miles of the tract in columns 3 & 4, PPP lending by Fintech firms in columns 5 & 6, and PPP lending in the first funding round in columns 7 & 8. Top 4 share is the share of deposits in branches within 2 miles of the tract that belong to one of the four largest U.S. banks. X_j is a vector of tract-level controls, including the logarithms of 2017 small business employment ($\leq$500 employees) and 2019 small business lending in the tract; the logarithm of the number of branches within 2 miles of the tract; and the shares of jobs in the tract that earn over \$3333 per month, earn under \$1250 per month, are held by a worker with a college degree, or are held by a nonwhite employee. Each specification includes county fixed-effects, and even-numbered specifications weight by tract small business employment. Standards errors, in parentheses, are clustered by county. $^{+,*,**}$ indicate significance at 10%, 5% and 1%, respectively.