Bank Relationships and the Geography of PPP Lending*

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Abstract

I study how bank relationships affected the timing and geographic distribution of Paycheck Protection Program (PPP) lending. Half of banks' PPP loans went to borrowers within 2 miles of a branch, mostly driven by relationship lending. Firms near less active lenders shifted to fintechs and other distant lenders, resulting in delays receiving credit but only slightly lower loan volumes. I estimate a structural model to fit the observed relationship between branch distance, bank PPP activity, and origination timing. I find that banks served relationship borrowers 5 to 9 days before other borrowers, an effect in line with reduced-form estimates using a sample of PPP borrowers with previous SBA lending relationships.

*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. To manage these hurdles, banks reportedly focused on providing credit to existing customers, for whom less due diligence is required before lending. This behavior raises the question: What happened when relationship credit was less available?

In this paper, I use geocoded data on the locations of bank branches and PPP borrowers to study the spatial distribution of PPP loan originations and how it relates to origination timing. As the majority of banks' small business lending is concentrated within a short distance of their branches, the 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 the role bank relationships played in supporting lending.

I present three findings pertaining to the relationship between borrower proximity, bank PPP activity, and origination timing. First, PPP lending was highly localized, particularly for relationship-oriented banks.[1] About half of bank loans overall, and two-thirds of loans from relationship-oriented banks, went to borrowers within 2 miles of a branch. Less relationship-oriented banks did more nonlocal lending. This result suggests that PPP lending was localized because prepandemic small business lending was. Between government guarantees removing the information-based advantages of local banks, and pandemic restrictions to on-site activities limiting the benefit of branch access, there was little reason to choose

[1] Relationship-oriented banks are banks where PPP lending was less than prepandemic small business lending. Banks for which this is not the case were more likely to have expanded significantly beyond relationship borrowers.

a nearby lender for a PPP loan absent an existing relationship. Consequently, the different geographic distribution of relationship and nonrelationship PPP lending can be exploited to examine the benefit of bank relationships.

Second, there is a U-shaped relationship between a bank's PPP activity and the average time a borrower needs to wait to receive a loan. The banks providing the shortest wait times are those whose total volume of PPP lending was comparable to the stock of prepandemic small business loans. Borrowers tended to face longer delays when their bank was less active in PPP (indicating bank-specific lending frictions) or very highly active (meaning a high share of borrowers were not existing clients).

Third, borrowers who obtained PPP loans from nearby lenders received credit earlier, particularly if their lender was more active in the program. Active 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, indicating that these banks did not expand beyond existing clients. Ultimately, the results suggest that there is a benefit to having a relationship with an active PPP lender.

I rationalize these three findings in a model where banks are heterogeneous in their PPP lending technology, borrowers face time costs to switching banks, and the spatial distribution of lending differs for relationship and nonrelationship loans. Banks with better processing technology originate loans faster and retain more of their relationship clients. However, once relationship clients are served, better technology then facilitates more nonrelationship lending, generating the U-shaped relationship between PPP intensity and average origination time. Nearby borrowers from active lenders receive credit earlier, on average, reflecting these loans disproportionately being relationship loans. When I estimate the model relating origination timing to the lending bank's proximity and PPP intensity, I find that nonrelationship borrowers had to wait an extra 5 to 9 days to receive credit, on average.

Finally, I present two additional pieces of evidence to validate the findings of the model.

First, I study the benefits of relationships for a sample of loans where preexisting relationships are observable. Specifically, I match borrowers who previously received SBA 7(a) loans with borrowers in the PPP data. For this sample, I can observe whether borrowers took out loans from their previous SBA lenders, and can thus assess the delays that come from switching lenders. The results are generally consistent with the model-estimated switching costs.

Second, I show that geographic differences in average origination timing are consistent with the hypothesized benefits of relationship lending. If there is a benefit to having a relationship with an active lender, and small business relationships are overwhelmingly with banks with nearby branches, then the benefits of a bank being active in the program should be localized around its branches. I show that census tracts near less-active banks faced delays in receiving loans. In these tracts, firms shifted borrowing towards fintechs or other distant lenders, consistent with Erel and Liebersohn (2020). However, there is only a small effect on loan volumes, indicating that borrowers ultimately were able to receive credit, albeit with a delay.

Taken together, these findings highlight the importance of bank relationships for PPP loan outcomes. Most borrowers received credit from nearby banks, suggesting they borrowed from banks with whom they had an existing relationship. Borrowers faced delays when credit was less available from local lenders, 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 were forgivable so long as businesses maintained 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 exhausted by April 16th. An additional $320 billion in funding was provided, enabling the Small Business Administration (SBA) 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.[2]

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 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

[2]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.

less affected by the pandemic (Granja et al., 2022).

While bank relationships appear to be important for 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., 2022) to analyze subsets of PPP borrowers for which information on relationships are available.[3] 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 (Erel and Liebersohn, 2020; Li and Strahan, 2021; Granja et al., 2022; Faulkender et al., 2023).[4]

I contribute to this literature in three ways. First, I document the spatial scale at which relationship lending occurred. I find that most PPP loans went to borrowers within a couple of miles, and I estimate a steep drop in the likelihood borrowers are relationship borrowers after that distance. This is a finer spatial scale than is normally studied in the literature, meaning that I can more narrowly identify probable relationship lenders than other papers that analyze geographic differences in supply conditions. Indeed, I show that the activity of banks within two miles of a census tract influence the timing and composition of lending relative to other tracts in the same county.

Second, I quantify the benefit of relationship lending, estimating that banks served relationship borrowers 5–9 days before nonrelationship borrowers, depending on their technology. By inferring the probability of an existing relationship from a borrower's distance from the lending bank, I am able to estimate the effects of relationship lending for the broad sample

[3] 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. (2022) use data from public firms in the PPP to document that relationship borrowers are more likely to get credit and get credit faster.

[4] 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. Li and Strahan (2021) show that banks allocate more PPP loans to counties where they did more small business lending before COVID. Granja et al. (2022) show that ZIP codes with more active banks had higher levels of PPP lending, though employment effects were modest. Faulkender et al. (2023) show that counties served more by community banks received credit earlier and experienced a smaller rise in unemployment.

of bank PPP loans. By doing this, I can sidestep some concerns about sample selection or representativeness that come with the analysis of small subsets of borrowers where relationships are observable (though I also validate my estimates with such a subsample of borrowers with prior SBA relationships).

Finally, I contribute to work analyzing delays in PPP loan receipt by estimating a model of the sources of these delays. Existing work shows that delays receiving PPP loans are associated with higher rates of financial distress (Denes et al., 2021), increases in business closures (Kurmann et al., 2022) and declines in employment (Doniger and Kay, 2023). The model allows me to make inference as to how the interplay of normally unobservable factors—bank technology, borrower switching costs, and bank relationships—drove differences in the timing of loan receipt.[5]

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.[6]

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

[5]Technology in the model is inferred based on a banks' lending relative to prepandemic relationship lending. Complementary papers provide insight into how factors such as previous SBA experience (Granja et al., 2022) or the suite of technological products utilized by the bank (Pogach and Kutzbach, 2022) contribute to such technological differences.

[6]This data is available here: `https://www.geocod.io/geocoded-ppp-loan-data/`.

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, I conduct a fuzzy-name match between originator names in the PPP data and institutions in the National Information Center's (NIC) Institution Directory to find the RSSD ID of the originating lender.[7] I use this bank identifier to match PPP loans to the branch locations of the lending bank in the SOD and compute the distance to the closest branch of that bank.[8] 89% of PPP loans match to the SOD data, with nearly all of the unmatched loans coming from nonbanks.

Bank PPP intensity The extent of a bank's PPP activity is measured by the ratio of PPP lending to prepandemic small business lending relationships. In the model in Section 4, banks with superior lending technology are able to process loans more quickly and retain/attract more borrowers relative to their stock of existing relationships. To reflect this, I measure PPP intensity as the ratio of 2020 PPP lending for bank b to a weighted average of outstanding small business loans and outstanding C&I loans in the 2019:Q4 Call Reports.[9] As the former likely excludes many eligible borrowers, while the latter includes loans to many firms that were too large to participate in PPP, my proxy for the relationship stock is an average of the two loan balance measures. I place a 90% weight on small business loans to equate the aggregate for the relationship stock proxy with total PPP lending. Namely, the measure of PPP activity is:

$$\text{PPP Intensity}_b = \frac{\text{PPP}_b}{.9 \times \text{SB Loans}_{b,19:Q4} + .1 \times \text{C\&I Loans}_{b,19:Q4}}$$

This 90% weighting simplifies the interpretation of some results, as it centers ln(PPP Intensity) around 0. However, this decision regarding the supply measure matters little;

[7]Some lender names in the PPP data can match to multiple banks. I disambiguate by selecting fuzzy name matches that also match on ZIP code, then state, then finally selecting the prospective match with the highest PPP lending volume.

[8]Distance is calculated using the haversine formula. The minimum distance is found using the BallTree module from scikit-learn.

[9]Small business loans are C&I loans with an original balance under $1 million dollars.

estimates are similar when measuring supply by PPP originations to total assets, PPP originations to small business loans, or using the PPP exposure measure of Granja et al. (2022).

Tract level data The loan level analysis uses controls for tract level labor market and small business loan market conditions from Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics Workplace Area Characteristics (LODES) and Community Reinvestment Act (CRA) data, respectively. LODES provides data on employment for 2010 census blocks, which I aggregate to the tract level.[10] The key variables of interest are the share of employment that is nonwhite, the earnings distribution of local employees, and total employment in firms with 500 or fewer employees (generally reflecting employment in PPP-eligible firms).[11] CRA includes information on the volume of loans to firms with less than $1 million in revenue by census tract.[12]

Additionally, for tract level analysis, I calculate the average ln(PPP intensity) of the banks with branches within 2 miles of a census tract, weighting by the deposits in those branches.[13] For this calculation, I exclude PPP lending in that particular tract from the numerator of the PPP intensity measure to avoid reverse causality whereby strong lending in a tract drives a high PPP intensity for a bank. As prepandemic small business lending was highly localized, this variable measures the likely availability of credit from relationship lenders in an area, and enables the analysis of how geographic differences in credit availability affected PPP outcomes at a fine spatial scale.[14]

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[10] I use the data on private jobs in 2017, as this is the most recent year that reports employment disaggregated by firm size. Alaska is missing for 2017, so I instead use 2016 data there.

[11] Earnings 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 by 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.

[12] I use data from 2019 in order to reflect prepandemic 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.

[13] Tract locations are measured by the centroids in the 2010 Census Gazetteer files.

[14] Outcomes considered include: PPP loan volumes, average days until origination, and the shares of PPP lending accounted for by fintech lenders or local lenders.

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 175 miles, reflecting a non-negligible share of loans being made independent of geography.

Regarding the supply measure, the median PPP intensity of the lending bank was almost 1.5 (PPP lending that is 50% greater than the stock of relationship loans). However, this reflects high-intensity banks appearing as lenders more frequently; the median is slightly above 1 at the bank level.

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 bank borrowers got loans before the first round of funding ran out.

Table 1: Summary Statistics

Variable	Description	Mean	sd	Percentile 25	Percentile 50	Percentile 75	N
Panel 1: Loan level Statistics							
$\text{Distance}_{i,b}$	Miles to nearest branch of lending bank	174.78	519.33	0.80	2.03	8.44	4,548,796
$\text{Local Branch}_{i,b}$	1 if $\text{Distance}_{i,b}$ <2 miles	0.50	0.50	0.00	0.00	1.00	4,548,796
PPP Intensity_{b}	$PPP_b/(.9SBL_b + .1CI_b)$	18.59	76.40	0.84	1.46	2.67	4,549,275
$\ln(\text{PPP Intensity}_{b})$	Logarithm of PPP Intensity_{b}	0.64	1.54	-0.17	0.38	0.98	4,549,275
Top 4_{b}	1 if lender is JPM, WFC, C or BAC	0.19	0.39	0.00	0.00	0.00	4,549,275
$\text{Days to Origination}_{i,b}$	Days between origination date and April 3rd	29.32	25.65	11.00	26.00	28.00	4,549,275
$\text{Round 1 Indicator}_{i,b}$	1 if originated by April 16th	0.31	0.46	0.00	0.00	1.00	4,549,275
$\ln(\text{Loan Amount})_{i,b}$	Logarithm of PPP loan balance	10.32	1.46	9.34	10.13	11.23	4,549,274
$\text{Small Firm}_{i,b}$	1 if business has fewer than 5 employees	0.54	0.50	0.00	1.00	1.00	4,549,275
$\text{Urban}_{i,b}$	1 if business has urban location	0.80	0.40	1.00	1.00	1.00	4,549,275
Panel 2: Tract level Statistics							
$\ln(\text{PPP Intensity})_{j}$	PPP intensity (exlcuding j) of local branches	-0.10	0.49	-0.41	-0.11	0.19	54,292
Top 4 Share_{j}	Top 4 deposit share within 2 miles	0.35	0.31	0.00	0.32	0.58	54,297
$\text{Days to Origination}_{j}$	Average days between origination date and April 3	35.36	12.38	26.90	33.28	41.18	53,889
Round 1 Share_{j}	Percent of loans originated by April 16	26.32	16.94	12.90	24.03	37.93	53,889
$\text{Local PPP Share}_{j}$	Percent of PPP Lending by banks within 2 miles	48.87	25.83	28.03	49.13	69.62	53,145
$\text{Fintech PPP Share}_{j}$	Percent of PPP Lending by fintechs	8.01	12.16	1.34	3.72	9.10	50,629
$\ln(\text{Total PPP})_{j}$	Logarithm of PPP lending in tract	15.08	1.36	14.26	15.16	15.98	53,889
$\ln(\text{Branches})_{j}$	Logarithm of branches within 2 miles	2.03	1.06	1.39	2.08	2.71	54,297
$\ln(\text{SB Lending})_{j}$	Logarithm of 2019 small business Lending	6.52	1.27	5.80	6.69	7.40	50,089
$\ln(\text{SB Emp})_{j}$	Logarithm of small business employment	6.25	1.14	5.58	6.32	7.01	53,604
Nonwhite_{j}	Nonwhite share of employment	0.24	0.17	0.12	0.21	0.32	53,620
$\text{Earnings} > \$3333_{j}$	Share jobs earning > \$3333 month	0.32	0.15	0.22	0.30	0.41	53,620
$\text{Earnings} < \$1250_{j}$	Share jobs earning < \$1250 month	0.30	0.12	0.22	0.30	0.37	53,620
College_{j}	Share workers w. college degree	0.25	0.08	0.19	0.24	0.30	53,617

3 Distance, PPP Intensity, and Origination Timing

This section documents three findings pertaining to the relationship between distance, the PPP intensity of the lending bank, and the time until origination. First, I show that PPP lending was highly localized, particularly for relationship-oriented banks. Second, I document a U-shaped relationship between PPP intensity and time-to-origination. Third, I demonstrate that borrowers received credit earlier if they are close to a branch of the lending bank, particularly if it has a high PPP intensity.

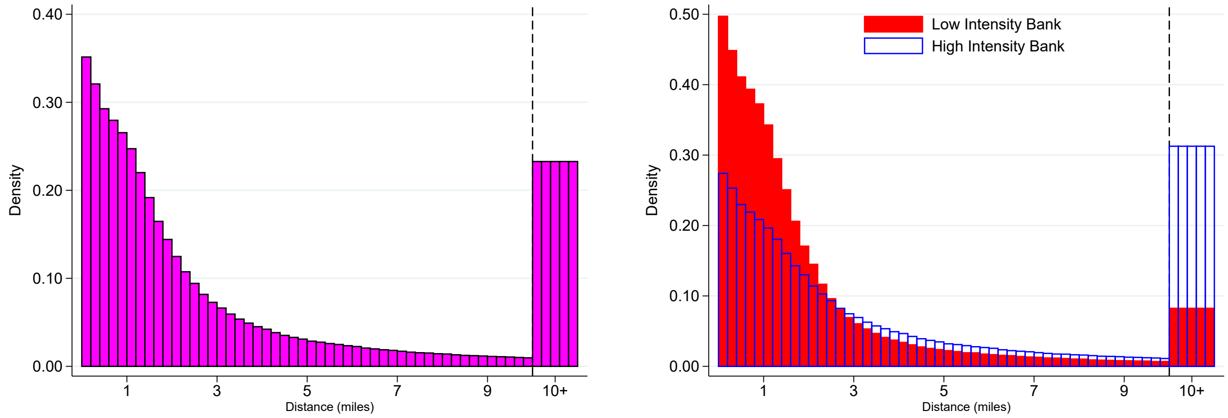
3.1 Relationships and Distance

Figure 1 plots histograms of the distance between PPP borrowers and the nearest branch of the lending bank. The left panel shows results combined across all bank loans. 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 prepandemic small business lending, with a bit more mass in the right tail driven by these online lenders.[15]

That PPP lending remained highly localized 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. Moreover, restrictions on branch operations due to the pandemic weakened the benefit of easy physical access to a bank

[15] 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



(a) Distribution of Distances

(b) Distribution by Bank PPP Intensity

Notes: This figure plots histograms 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 left panel pools all bank PPP loans, while the right separates banks with a high and low PPP intensity (the blue and red bars, respectively).

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 the reasons for favoring nearby firms were substantially weakened.

The right panel of Figure 1 provides more direct evidence for local lending being relationship driven. While the relationship status of a given loan is hard to ascertain, if a bank has a high ratio of PPP lending to prepandemic small business lending, then their PPP portfolio likely contains a higher share of nonrelationship loans. The histogram plots the distance distribution separately for loans from banks with a PPP intensity under 1 (which presumably predominantly served existing clients), and those with an intensity above 1 (whose portfolios would contain more nonrelationship loans).

The results are consistent with relationship loans being more localized. Low-intensity banks have a much higher share of loans going to borrowers within two miles (68%, compared to only 40% for high-intensity banks). High-intensity banks are slightly more likely to originate loans that are between 3 and 10 miles away, and much more likely to originate loans that are over 10 miles away. These results are not due to regional differences, for instance due to density, as results are similar using the residual distance after accounting for loan controls and census tract fixed effects (see Appendix Figure A1).

3.2 PPP Intensity and Origination Timing

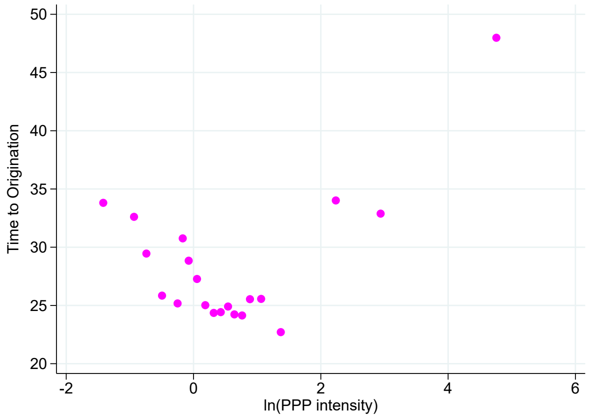
How does PPP intensity relate to origination timing? There are several mechanisms at play, working in different directions. On one hand, as discussed in the previous subsection, high-intensity banks likely did a higher share of their lending to nonrelationship customers. As relationship loans are quicker to originate—search costs have been paid and initial due diligence already conducted—banks that just focused on existing relationships may be able to process loans faster. On the other hand, banks with superior processing technology may originate loans faster and thus attract more clients, resulting in wait times that decrease in PPP intensity.

Figure 2 presents the results of binscatter regressions of time-to-origination on the logarithm of the lending bank's PPP intensity.[16] The left panel is unweighted, while the right weights by the inverse of the number of loans from the lending bank in order to reduce the influence the largest lenders have on the estimates. The figures show a U-shaped relationship between a bank's PPP intensity and the time borrowers have to wait to receive a loan. Banks with an ln(PPP Intensity) slightly above 0—meaning PPP lending just exceeded prepandemic small business lending—generally provided the shortest average wait times. Banks with PPP lending well above or below this level tended to have much longer average wait times.

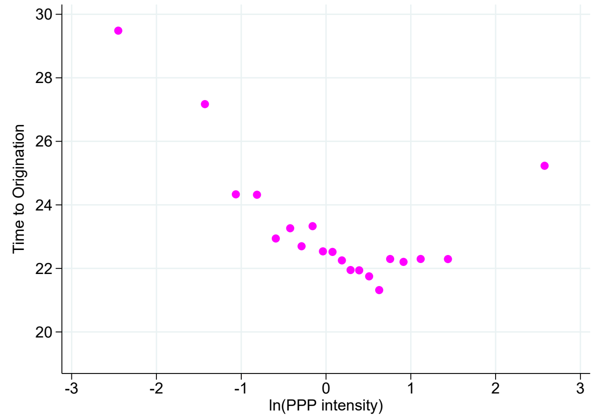
This pattern is consistent with the aforementioned competing mechanisms. Banks who did less PPP lending than prepandemic small business lending likely predominantly served relationship clients, meaning that marginal differences in PPP activity provide little infor-

[16] Binscatters are constructed using the Binsreg command in Stata (Cattaneo et al., 2019), controlling for loan size, a small firm indicator, census tract characteristics (an urban indicator, the share of employees that are nonwhite, and the logarithms of prepandemic small business employment and small business lending), and county fixed effects.

Figure 2: Wait Times by PPP Intensity



(a) Unweighted



(b) Inverse Count Weighted

Notes: This figure plots binscatter regressions of time-to-origination on the log PPP intensity of the lending bank for 2020 bank PPP loan originations. Controls include the size of the loan, an indicator for whether the firm has fewer than 5 employees, census tract characteristics (an urban indicator, the share of employees that are nonwhite, and the logarithms of prepandemic small business employment and small business lending), and county fixed effects. The left panel is unweighted, while the right panel weights by the inverse of the number of PPP loans from the lending bank.

mation about relationship status. If most loans are relationship loans, we would expect a downward sloping relationship between PPP intensity and time-to-origination, as faster lenders are able to retain more of their clients. However, for banks with a PPP intensity above 1, increases in PPP intensity indicate more nonrelationship loans, and thus delays in the average time of loan receipt. This explanation for the U-shaped relationship is formalized in the model in Section 4.

3.3 Distance and Origination Timing

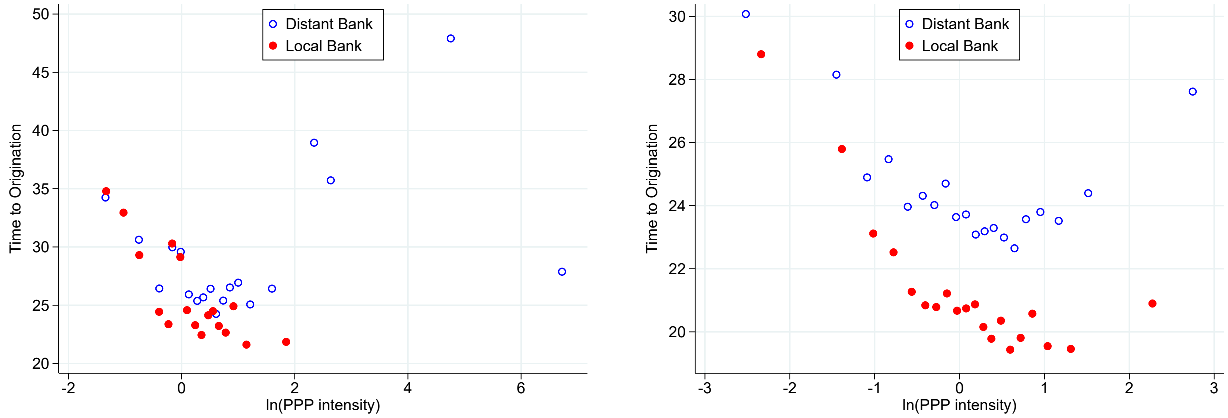
The final evidence motivating the model pertains to the relationship between distance and origination timing. Section 3.1 showed that relationship-oriented PPP lenders concentrated lending within two miles of their branches. Section 3.2 showed that the relationship between PPP intensity and origination timing was non-monotonic, likely due to a higher share of nonrelationship loans at the largest PPP lenders. Now I analyze the interaction of distance and proximity; if the delays receiving loans at high-intensity banks were driven by nonrelationship loans, such effects should be moderated by proximity (as such nearby loans are more likely to be relationship loans.)

Figure 3 repeats the binscatter regressions from Figure 2, but disaggregating by whether loans are to borrowers within 2 miles of a lender. The figures demonstrate that the upward sloping relationship between wait times and PPP intensity are generally driven by non-local lending. Wait times are essentially monotonically decreasing in PPP intensity for nearby borrowers, but U-shaped for more distant borrowers. For banks with a low PPP intensity, there is not much of a difference in origination timing for local and non-local borrowers. This result is consistent with timing differences across originators reflecting relationship lending; if a banks seems to not have expanded lending beyond relationship clients, proximity is less informative about relationship status. However, banks with PPP lending exceeding estimates for their relationship stock are more likely to have a notable share of nonrelationship loans, making proximity more informative. For banks with a log PPP intensity around 1 (meaning PPP lending that is almost triple the relationship stock), nearby borrowers receive loans about 4 days before distant borrowers.

These results are also apparent in regressions. Appendix Table A1 presents estimates from regressing wait times on ln(PPP intensity), an indicator for whether a borrower is within 2 miles, and interactions of ln(PPP intensity) with itself and the local dummy.[17] Overall, borrowers from nearby banks get credit about a day earlier than other borrowers, with the benefit of using a local bank increasing in the PPP intensity of that bank. The quadratic term corroborates that there is a U-shaped relationship between PPP intensity and origination timing. Expected wait times are minimized at a PPP intensity around 2.3 for distant borrowers and 4.0 for nearby borrowers (1.4 and 4.8 in unweighted regressions). Patterns are similar if origination timing is measured by an indicator for whether the loan was originated before the first round of funding was exhausted (Appendix Table A2).

[17] All specifications include county and 3-digit NAICS fixed effects, and control for loan size, whether the business has fewer than 5 employees, and tract characteristics (an urban indicator, the share of employees that are nonwhite, and the logarithms of prepandemic small business employment and small business lending). Regressions are either unweighted, or weight by the inverse of the number of PPP originations at the bank.

Figure 3: Wait Times by Bank Proximity and PPP Intensity



(a) Unweighted

(b) Inverse Count Weighted

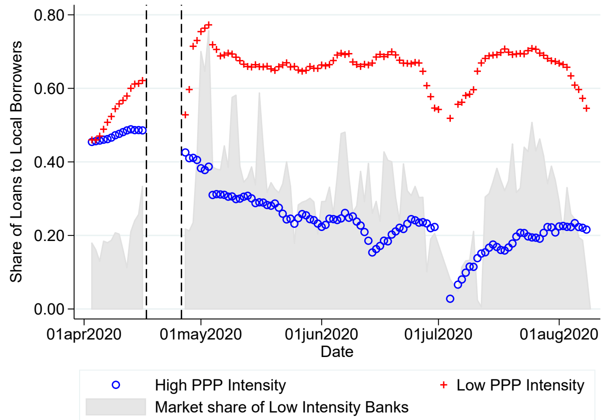
Notes: This figure plots binscatter regressions of time-to-origination on the log PPP intensity of the lending bank for 2020 bank PPP loan originations. Controls include the size of the loan, an indicator for whether the firm has fewer than 5 employees, census tract characteristics (an urban indicator, the share of employees that are nonwhite, and the logarithms of prepandemic small business employment and small business lending), and county fixed effects. The left panel is unweighted, while the right panel weights by the inverse of the number of PPP loans from the lending bank. Red dots pertain to loans to borrowers within 2 miles of a branch of the lending bank, while hollow blue dots pertain to loans to more distant borrowers.

3.4 Discussion

To summarize the results so far: (1) nonrelationship PPP lending was more geographical dispersed than relationship lending, making proximity informative as to a loan's relationship status; (2) banks with a very high amount of PPP lending relative to prepandemic small business lending had longer wait times, consistent with there being delays associated with switching to nonrelationship lenders; and (3) wait times decrease in PPP intensity for nearby borrowers, suggesting that there is a benefit to having a relationship with an active lender, even if there isn't a clear benefit from simply borrowing from one.

This set of results is consistent with banks prioritizing existing relationships first, and the more active PPP lenders then moving on to new clients later. Figure 4 presents evidence that this is the case. The figure plots the share of loans made to local borrowers by bank PPP intensity (defined by whether or not PPP intensity is above 1), as well as the market share of the low-intensity banks, over time. Banks that were less active in PPP (in red) predominantly served nearby clients throughout the program, with the share of loans to

Figure 4: Share of Local Lending over Time



Notes: This figure shows the share of loans by date made by banks with branches within 2 miles of the borrower. Red crosses plot results for low-intensity banks (PPP intensity under 1), while blue circles plot results for high-intensity banks. The grey area shows the share of loans made by low-intensity banks. Loans originated within 2 days of the date listed on the x-axis are pooled in order to reduces noise, for example, due to low volumes during weekends.

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 blue) 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.

Overall this figure paints a similar picture to other results. Namely, existing clients of major PPP lenders receive credit earlier, as evidenced by these lenders' high market share and 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 nonrelationship banks faced delays, as evidenced by the higher rates of nonlocal lending later in the program.

4 Theory

This section presents a model to explain the patterns documented in Section 3. I estimate the model to fit observed differences in the timing and spatial distribution of PPP loan originations across banks. I then use these estimates to quantify the costs of switching away from relationship lenders.

4.1 Model

Supply of PPP Loans Banks had little discretion over the terms of PPP loans; loan terms were set by the program and were essentially uniform across borrowers, besides loan size, which was mechanically determined by a firm's 2019 payroll. Consequently, I model banks as competing on how quickly loans are processed.

Suppose that bank b takes on average $T_b(L) = \tau_b(\frac{L}{R_b})^\gamma$ days to process their first L PPP loans, where τ_b measures the time that it would take to process their R_b relationship clients and γ reflects congestion effects. $\gamma = 0$ means that all loans are processed in τ_b days regardless of where they are in the queue, while $\gamma = 1$ corresponds to loans being processed sequentially at a rate of $\frac{R_b}{2\tau_b}$.

Banks serve existing relationship clients first, before moving on to nonrelationship clients, and do not distinguish between borrowers within these pools. As a result, relationship and nonrelationship clients will have different expected wait times, denoted T_b^R and T_b^N, respectively. In equilibrium, since banks prioritize existing clients, any bank that does nonrelationship lending will also be able to retain all of their existing clients.[18] Consequently, the amount of relationship PPP lending will be $\min\{L_b, R_b\}$, where L_b is a bank's total PPP lending. The lending technology then implies that the expected processing time for a relationship loan will be $T_b^R = \tau_b(\frac{\min\{L_b,R_b\}}{R_b})^\gamma$. T_b^N will be such that the average processing time for L loans is the average for relationship and nonrelationship borrowers, weighted by their

[18]Since borrowers choose the nonrelationship lender with the best processing time, T_b^N is equalized for all banks that do nonrelationship lending. Relationship prioritization results in $T_b^R < T_b^N$, so borrowers would never switch from a bank that does nonrelationship lending.

respective shares. Defining $\rho_b \equiv \frac{L_b}{R_b}$ as the ratio of PPP loans to relationship borrowers, T_b^N must satisfy:

$$\tau_b \rho_b^{\gamma} = \rho_b^{-1}\tau_b + (1-\rho_b^{-1})T_b^N \text{ if } \rho_b > 1. \tag{1}$$

where τ_b and T_b^N are the processing times for relationship and nonrelationship loans, respectively, and ρ_b^{-1} is the share of loans to relationship borrowers.

Demand for PPP Loans We now derive the number of loans made by a bank as a function of their processing times. If a firms decides to leave their relationship bank, they choose the lender with the lowest expected processing time. In equilibrium, all nonrelationship loans will have the same expected processing time, denoted T.

Demand from relationship borrowers is determined by borrowers' decision to accept either the time offered by their relationship bank or the processing time of T available to nonrelationship borrowers. Borrowers face a heterogeneous switching cost, which creates a markup $\mu_i \geq 1$ over T in the time to receive a nonrelationship loan, reflecting switching and on-boarding time. Let μ_i be pareto distributed with shape parameter α (i.e. μ_i has a cdf $1-\left(\frac{1}{\mu}\right)^{\alpha}$ for $\mu \geq 1$). If $\tau_b > T$, the bank cannot process all of their relationship borrowers in a timely enough manor to induce them all to stay with the bank. In this case, the volume of lending will be such that:

$$L_b = R_b \times Pr(T_b^R < \mu_i T) = R_b(\frac{T}{T_b^R})^{\alpha} \text{ if } \tau_b > T. \tag{2}$$

Equilibrium Equilibrium loan volumes and processing times are determined by the intersection of the supply curves (determining the time to process a given number of loans) and the demand curves (determining the number of borrowers who choose to take out a PPP loan given a particular processing time).

If $\tau_b > T$, the bank operates on the downward sloping portion of the demand curve, as some relationship clients with low switching costs leave the bank. Inverting equation (2), we get that the time to process relationship loans is $T_b^R = \rho_b^{\frac{-1}{\alpha}} T$ where $\rho_b < 1$.

If $\tau_b < T$, all relationship borrowers stick with their bank and receive an expected time to origination τ_b. For these banks, the number of loans is determined by how many loans the bank is capable of making while offering a processing time of T for nonrelationship borrowers. Substituting T in for T_b^N in equation (1), we can solve for $\tau_b = T_b^R = \frac{\rho_b - 1}{\rho_b^{1+\gamma} - 1} T$.[19]

These expressions all derive the expected time that it takes to receive a loan as a function of ρ_b and a borrower's relationship status:

$$\mathbb{E}(T_{i,b}|R_{i,b}, \rho_b) = T \times \begin{cases} \rho_b^{\frac{-1}{\alpha}} & \text{if } \rho_b < 1 \text{ and } R_{i,b} = 1 \\ \frac{\rho_b - 1}{\rho_b^{1+\gamma} - 1} & \text{if } \rho_b > 1 \text{ and } R_{i,b} = 1 \\ \bar{\mu} T & \text{if } \rho_b > 1 \text{ and } R_{i,b} = 0 \end{cases} \tag{3}$$

where $\bar{\mu}$ is the expected switching cost for borrowers that switch lenders, T is the equilibrium time to process nonrelationship loans, and $R_{i,b}$ denotes the event that i has a relationship with b.

Distance Estimating equation (3) directly would require information on which borrowers received credit from a relationship bank. Since this information is generally unavailable, I instead take advantage of the observation from Figure 1 that relationship and nonrelationship loans appear to have different geographic distributions. By estimating how the probability a lender is a relationship lender differs over space, I can express equation (3) in terms of borrower-lender distance rather than $R_{i,b}$.

Assume that relationship and nonrelationship loans have different geographic distributions. Let $f^R(d)$ and $f^N(d)$ denote the distribution of distances between banks and their relationship and nonrelationship clients, respectively, which are assumed to be independent of ρ_b and satisfy the monotone likelihood ratio property (MLRP) $\lambda'(d) > 0$ for $\lambda(d) \equiv \frac{f^N(d)}{f^R(d)}$.

[19] T_b^R is indeterminate if $\rho_b = 1$, taking values in the range $[\frac{T}{1+\gamma}, T]$, reflecting the range of τ_b that is low enough to serve all relationship customers, but high enough to not attract nonrelationship customers after. Since there are no observations in the data with this intensity, it does not matter for the estimation.

In words, borrowers that are further from a bank are more likely to be nonrelationship borrowers.

We are interested in solving for the probability that a loan is to a relationship borrower based on the distance to the lending bank ($d_{i,b}$) and the share of PPP loans going to relationship borrowers ($\min\{\rho_b^{-1}, 1\}$). From Bayes' rule, this probability can be solved as:[20]

$$\begin{aligned} P(R_{i,b} = 1 | d_{i,j}, \rho_b) &= \frac{f(d_{i,b}|R_{i,b} = 1, \rho_b) P(R_{i,b} = 1|\rho_b)}{f(d_{i,b}|\rho_b)} \\ &= \Big(1 + (\rho_b - 1)\lambda(d_{i,b})\Big)^{-1} \qquad \text{if } \rho_b > 1 \end{aligned} \tag{4}$$

$P(R_{i,b} = 1|d_{i,j}, \rho_b) = 1$ if $\rho_b < 1$ since the bank only does relationship loans.

Combining equations (3) and (4), we get the following expression for the expected time to loan receipt as a function of a bank's PPP intensity and the distance to the lending bank:

$$\mathbb{E}(T_{i,b}|d_{i,b}, \rho_b) = T \times \begin{cases} \rho_b^{\frac{-1}{\alpha}} & \text{if } \rho_b < 1 \\ \bar{\mu} - \underbrace{\Big(1 + (\rho_b - 1)\lambda(d_{i,b})\Big)^{-1}}_{P(R_{i,b}=1|d_{i,b},\rho_b)} \underbrace{\left(\bar{\mu} - \frac{\rho_b - 1}{\rho_b^{1+\gamma} - 1}\right)}_{\text{Benefit of Relationship}} & \text{if } \rho_b > 1 \end{cases} \tag{5}$$

Relationship to Empirical Results Equation (5), combined with the MLRP assumption for $\lambda(d)$, delivers the three empirical results presented in Section 3. First, PPP lending is more localized for relationship-oriented banks as MLRP implies that the distance distribution for nonrelationship borrowers, $f^N(d)$, first-order stochastically dominates the distribution for relationship borrowers, $f^R(d)$. This assumption thus implies more localized lending for the banks that do not extend beyond relationship clients (banks with a $\rho_b < 1$).

Second, Equation (5) produces U-shaped relationship between between a bank's PPP intensity (ρ_b) and the average timing of loan origination. As PPP intensity rises to 1, the average time to origination falls to T. This pattern is driven by banks with better lending

[20] The second line comes from the fact that $f(d_{i,b}|\rho_b) = \rho_b^{-1} f^R(d) + (1 - \rho_b^{-1}) f^N(d)$, $f(d_{i,b}|R_{i,b} = 1, \rho_b) = f^R(d)$ and $P(R_{i,b} = 1|\rho_b) = \rho_b^{-1}$ when $\rho_b > 1$.

technology offering faster processing times, losing fewer clients to nonrelationship lenders, and thus doing more lending. However, as the intensity rises from 1, the average time rises from $\frac{T}{1+\gamma}$ and asymptotes to $\bar{\mu}T$. The eventual reversal reflects a greater share of nonrelationship loans, for which origination times include switching costs.

Third, there is a benefit to geographic proximity to active lenders. Differentiating equation (5) with respect to $d_{i,b}$. We get that if $\rho_b > 1$ then:

$$\frac{\partial\, \mathbb{E}(T_{i,b}|d_{i,b},\rho_b)}{\partial d_{i,b}} = \underbrace{T\Big(\bar{\mu} - \frac{\rho_b - 1}{\rho_b^{1+\gamma} - 1}\Big)}_{\text{Benefit of Relationship}} \underbrace{\Big(1 + (\rho_b - 1)\lambda(d_{i,b})\Big)^{-2}(\rho_b - 1)\lambda'(d_{i,b})}_{\frac{\partial P(R_{i,b}=0|d_{i,b},\rho_b)}{\partial d_{i,b}}} > 0$$

Namely, the expected time to origination rises with distance because distant lenders are less likely to be relationship lenders. There is no such effect for banks with $\rho_b < 1$ because they only serve relationship clients.

4.2 Estimation

Estimation of $P(R_{i,b} = 1|d_{i,b}, \rho_b)$ From equation (4), the probability that loan is from a relationship lender is a function of ρ_b and $\lambda(d_{i,b})$. ρ_b is the ratio of 2020 PPP lending to prepandemic small business lending in the Call Reports for bank b (as discussed in Section 2). I estimate $\lambda(d)$ in order to match the distributions of loan distance for banks with $\rho_b < 1$ and $\rho_b > 1$. Since banks with $\rho_b < 1$ only make relationship loans, the kernel density estimate of the distance distribution provides an estimate of $f^R(d)$. Banks with a $\rho_b > 1$, make both relationship and nonrelationship loans, thus their $f(d|\rho_b > 1)$ is a mixture of the relationship and nonrelationship distributions, with a weight of $\mathbb{E}_i(\rho_b^{-1}|\rho_b > 1) = 0.502$ on $f^R(d)$. Consequently, $f^N(d)$ is estimated as:

$$\hat{f}^N(d) = \frac{\hat{f}(d|\rho_b > 1) - 0.502\hat{f}^R(d)}{1 - 0.502}$$

where $\hat{f}(d|\rho_b > 1)$ and $\hat{f}^R(d)$ are the kernel density estimates of distance for high- and low-intensity lenders, respectively. Taking the ratio of $\hat{f}^N(d)$ and $\hat{f}^R(d)$ gives an estimate of $\lambda(d)$.

The left panel of Figure 5 plots these kernel density estimates. The red-line shows the distribution for low-intensity lenders. The density is maximized around a distance of 1 mile, but falls sharply for distances over 2 miles. The distribution for high-intensity lenders is shifted to the right, and has notably less mass under 2 miles (the typical distance range for a small business client) and more mass in the right tail. The implied distribution for nonrelationship loans, shown in grey, is shifted further to the right, reflecting the fact that some loans made by high-intensity banks are relationship loans and assumed to follow a similar geographic distribution as those from low-intensity lenders.

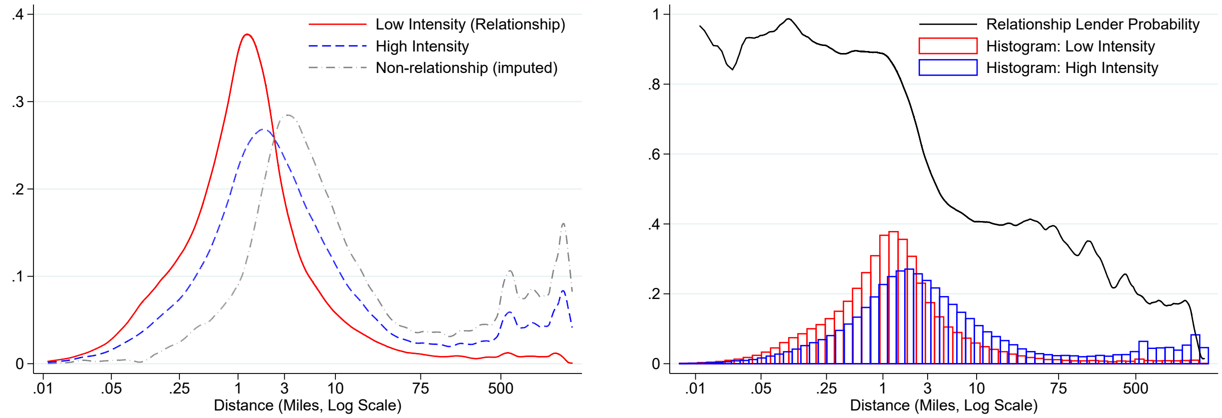
The right panel plots the probability that a lender is a relationship lender by distance, determined by the ratio of the estimated PDFs for nonrelationship and relationship loans. The probability hovers around 90% for a distance of up to a mile, then falls to 40% around a distance of 10 miles, and declines further to below 20% for loans over 500 miles away. The sharp decline around 2 miles makes that a useful reference point; about 88% of bank PPP loans within that distance are estimated to be relationship loans, compared to only 44% of loans beyond that distance.

Parameter Estimation Equation (5) defines the expected time to origination as a function of ρ_b, $\lambda(d_{i,b})$, and parameters (μ, T, γ, and α). These parameters are estimated by nonlinear least squares:

$$\text{Time-to-Origination}_{i,b} = \mathbb{E}(T_{i,b}|d_{i,b}, \rho_b) + (X_i'\beta)^+ + \varepsilon_{i,b}$$

where Time-to-Origination$_{i,b}$ is the number of days to origination for borrower i, $\mathbb{E}(T_{i,b}|d_{i,b}, \rho_b)$ comes from substituting ρ_b and $\hat{\lambda}(d_{i,b})$ into equation (5), and X_i is a vector of controls meant to capture borrower-specific factors that may affect origination timing beyond differences in

Figure 5: Distance and Relationship Lending



(a) Distances Distribution By Lender Type (b) Relationship Lender Probability

Notes: The left chart plots kernel density estimates of the distribution of loan distances for banks with a high- and low-PPP intensity (dashed blue and red lines, respectively). The grey line shows the implied distribution for nonrelationship loans. The line in the right figure plots the estimated probability that a loan is from a relationship lender by distance.

bank processing times and borrower switching costs. As the controls are meant to account for differences in the time to application, whereas $\mathbb{E}(T_{i,b}|d_{i,b}, \rho_b)$ is meant to capture differences in processing times after application, I restrict $X_i'\beta$ to be weakly positive.[21] Since the parameters of interest reflect bank-specific origination timing, I weight by the inverse of the number of PPP loans originated by b to reduce idiosyncratic noise from prominent PPP lenders. The sample of loans excludes firms with fewer than 5 employees, as such firms were less likely to be immediately aware of the program, and thus variation in the timing of loan receipt is less likely to reflect differences in bank processing times.[22]

4.3 Results

Estimates from this specification are in Table 2. The first column presents estimates from the baseline specification, while the next three columns, relative to the baseline specification,

[21] X includes loan size and the following tract controls: an urban indicator, the share of employees that are nonwhite, and the logarithms of prepandemic small business lending and employment.

[22] Over 20% of businesses with fewer than 5 employees were unaware of the program as of the time the initial funding was exhausted, whereas the vast majority of larger businesses were aware of it within a couple days of opening (Humphries et al., 2020).

Table 2: Parameter Estimates

T	9.768	13.625	13.930	15.078
$\bar{\mu}$	1.426	1.317	1.311	1.048
γ	0.088	0.046	0.045	0.694
α	3.778	4.287	4.765	4.691
Weighted	X	X	X	
Application Time	$(X_i'\beta)^+$	0	$(X_i'\beta)$	$(X_i'\beta)^+$
Relationship Benefit (days)	5.0 - 9.1	4.9 - 8.5	4.9 - 8.6	6.9 - 15.7

Notes: This table presents estimates from the equation:

$$\text{Time-to-Origination}_{i,b} = \mathbb{E}(T_{i,b}|d_{i,b}, \rho_b) + (X_i'\beta)^+ + \varepsilon_{i,b}$$

where Time-to-Origination$_{i,b}$ is the number of days until origination for loan i, $\mathbb{E}(T_{i,b}|d_{i,b}, \rho_b)$ is the expected processing time from equation (5) given the bank-borrower distance and bank PPP intensity, and $(X_i'\beta)^+$ is a control for application time, which is restricted to be weakly positive in the baseline specification. The X vector includes the log loan amount, and the following tract level controls: the nonwhite employment share, the logarithm of prepandemic tract small business employment, the logarithm of prepandemic small business lending, and an urban indicator. The specification is weighted by the inverse of the number of PPP originations at bank b. Columns 2-4 make the following alterations to this baseline specification: Column 2 omits the controls, column 3 removes the restriction that time to application is positive, column 4 is unweighted.

omit the application time control (column 2), remove the restriction that application time is weakly positive (column 3), and remove the inverse loan count weights (column 4).

The primary object of interest is the benefit of borrowing from a relationship bank, defined as the difference in the average time-to-origination between a bank's nonrelationship and relationship borrowers. From equation 5, we can see that this depends on three variables. The benefit of relationship borrowing scales with T, reflecting general processing times. The benefit is also increasing in $\bar{\mu}$, as higher average switching costs raise the cost of leaving the relationship bank, and γ, as higher congestion increases the cost of being deprioritized relative to relationship borrowers. The bottom row of Table 2 plots the range of benefits, where the lower bound is the benefit of a relationship with a bank that is on the margin of engaging in nonrelationship lending (the right limit as $\rho \to 1$), while the upper bound is the benefit at the bank with the highest PPP intensity in the sample.

While parameter estimates vary a fair amount, the ultimate estimate of the benefit of relationship borrowing is fairly stable. In the baseline specification, the estimates imply that banks serve relationship clients between 5 and 9 days earlier than nonrelationship clients. In columns 2 and 3, which exclude controls for application time or don't restrict that time to be positive, estimates for T rise, but this is offset by lower estimated switching costs and congestion costs. Ultimately, the range of benefits from relationship borrowing are little changed. In column 4, where the results are unweighted, estimated relationship benefits rise to be from 7 to 16 days. In this specification, delays are attributed more to congestion costs than switching costs, in order to better hit the slow origination times at banks with the highest PPP intensities. While the unweighted specification implies more notable relationship benefits at the top of the PPP intensity distribution, the estimated effect for the more typical PPP intensities is only a couple of days higher than those in the unweighted results.

5 Relationships for SBA Borrowers

The previous results estimate the benefit of relationship borrowing by inferring the probability of a preexisting relationship based on the lending bank's proximity and PPP intensity. To increase confidence in these estimates, I now use name-matched SBA 7(a) loan data to study the benefits of relationship lending in a sample of PPP loans for which a preexisting bank relationship is known.

5.1 Data and Name Matching

In order to identify whether borrowers are using relationship banks, I use microdata from the SBA's 7(a) program to identify PPP borrowers with previous SBA loans.[23] I use data on SBA loans originated from 2010 to 2019, and name match by firm name, blocking on the firm's ZIP code. This process identifies about 139,00 SBA borrowers in the 2020 PPP data, 99% of which have lender names that match to an originator in the PPP data, and 91% of

[23]SBA data is available here: https://data.sba.gov/dataset/7-a-504-foia.

which match a bank PPP originator. Roughly half of these successfully-matched PPP loans have the same PPP and SBA originator. These loans are identified as relationship loans.

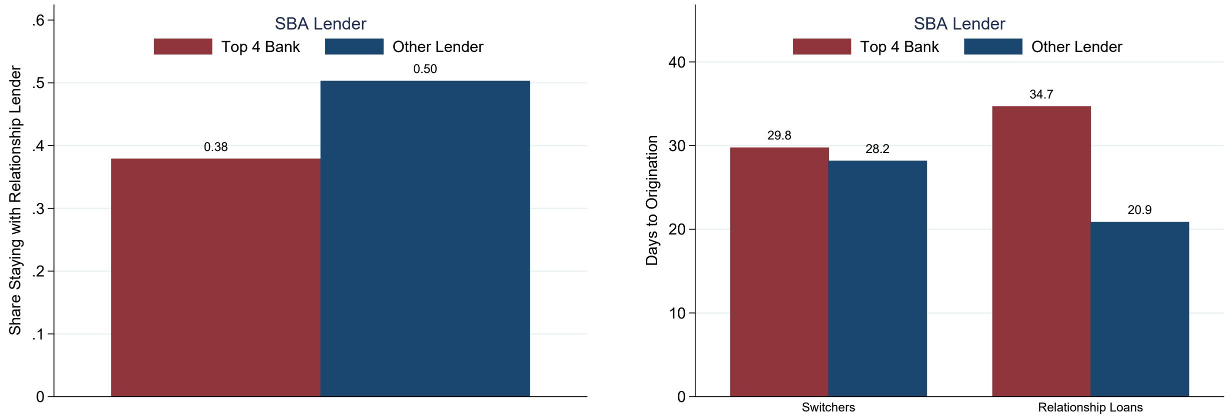
While the SBA data is useful for providing a sample of small businesses for which prepandemic relationships are known, there are a couple of limitations involved. First, it may be unrepresentative of other small business relationships. SBA loans are partially guaranteed by the government, possibly moderating screening/monitoring incentives, and facilitating more distant lending. For example, the largest SBA lender by volume is Live Oak, a branchless bank that specializes in remote lending (Di and Pattison, 2020). Additionally, SBA relationships may differ from other relationships as lenders necessarily have access to and familiarity with the SBA's application portal, facilitating the provisioning of PPP loans (Granja et al., 2022). Second, firms may have multiple relationship, and while SBA relationships can be observed, other relationships cannot. Thus, "nonrelationship" loans in this analysis may still be relationship loans even if the bank differs from the one making the SBA loan. Nonetheless, this data provides a useful complement to the other analysis, as bank relationships can be directly observed rather than inferred by borrower location.

5.2 SBA Relationships and Origination Timing

Before analyzing differences by PPP intensity, Figure 6 shows how PPP outcomes differed for borrowers that previously took out an SBA loan from one of the top 4 U.S. banks by assets. 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., 2022).

The left panel plots the shares of borrowers who took out a PPP loan from their relationship lender. The top 4 banks retained 38% of their SBA clients, compared to 50% retention for other SBA lenders. The right panel shows that relationship borrowers from the top 4 banks had to wait longer to receive credit than other borrowers, thus providing an explanation for why clients of the top 4 banks disproportionately sought PPP loans from

Figure 6: PPP Outcomes by Previous SBA Lender Type



(a) Share of Relationships Retained

(b) Origination Time

Notes: These charts plot the share of borrowers who take out a PPP loan from their previous SBA lender (left) and the average time-to-origination (right) by whether or not borrowers use their previous SBA lender. Red bars show results for PPP borrowers that took out an SBA loan from a top 4 bank, while blue bars show results for borrowers with relationships from other SBA lenders.

other lenders. Relationship loans at the top 4 banks had an average time to origination of 35 days, compared to only 21 days for other relationship lenders. Clients of the top 4 banks also faced worse delays when they switched to new lenders, although the difference was not as pronounced. Among the borrowers that switched to a PPP lender that was different from their SBA lender, clients of the top 4 banks had to wait about 30 days, while clients of other lenders had to wait about 28 days.[24]

Table 3 similarly documents the interplay between bank relationships, bank PPP intensity, and PPP origination timing, but with regressions of the type described in Section 3.3. The regressions predict the number of days until a loan is originated as a function of the lending bank's PPP intensity, indicators for whether the PPP loan is from a nearby bank or a relationship SBA lender, and pairwise interactions of these variables.

The most consistent result in the table is that relationship borrowers receive credit earlier, particularly if their bank is an active PPP lender. The coefficient of -3.75 on $\text{Relationship}_{i,b}$ means that a non-local borrower from a bank with a PPP Intensity of 1 is expected to wait

[24]This result is consistent with the model; clients at lower intensity banks are willing to switch lenders at higher switching costs, resulting in higher average wait times.

3.75 days less on average if their PPP lender is their previous SBA lender. The benefit to relationship clients is more pronounced for more active lenders, as can be seen by the negative coefficient on the interaction between the relationship indicator and the PPP intensity measure. For a bank with a ln(PPP Intensity)$_b$ = 2 (around the 95th percentile of lenders) relationship clients are expected to receive credit 11.2 days earlier.

Columns 2 and 4 additionally add PPP lender fixed effects, and columns 3 and 4 weight by the inverse of the number of loans from the lender (within the matched sample). These specifications continue to predict notable benefits to relationship clients, particularly those of active PPP lenders, though the range of benefits is less expansive. Across these 3 specifications, relationship clients are expected to receive credit 3.2 to 5.9 days earlier if their bank has a ln(PPP Intensity)$_b$ = 0, and 7.7 to 8.6 days earlier if ln(PPP Intensity)$_b$ = 2. These results, in particular the weighted results in the last two columns, are quite similar to the range of benefits implied by the baseline model estimates (benefits from 5.0 to 9.3 days).[25]

The estimates indicate that proximity still relates to origination timing, but the results are not as robust. In three of the four specifications, borrowers using a local bank receive credit slightly more than a day earlier than distant borrowers (assuming ln(PPP Intensity)$_b$ = 0 and the lender is not the SBA lender).[26] Again, using a nearby bank is more beneficial if that bank is a more active PPP lender. These results are consistent with banks having multiple relationships, so even those who "switch away" from their relationship SBA lender benefit from proximity, as those banks are more likely to be another relationship lender. However, the benefit of using a local branch only accrues to non-SBA-relationship borrowing. If a borrower uses their SBA lender, there is no marginal benefit to it being a local lender, consistent the effects of proximity being driven by relationships as opposed to proximity itself.

[25]I consider the upper range here to reflect the 95th percentile of PPP intensity, whereas in Table 2 the upper range is determined by the highest PPP intensity in the sample. I do this because the predictions from the regression specification assume effects are linear in ln(PPP Intensity), making extrapolation to extreme values more problematic than in the model where effects are concave in the right tail.

[26]The positive coefficient in the unweighted specification without the lending bank fixed effect is driven by the top 4 banks, which predominantly served nearby clients and were slow to extend credit.

Table 3: SBA Relationships and Origination Speed

	Days to Origination			
	(1)	(2)	(3)	(4)
Relationship$_{i,b}$	-3.67**	-3.13**	-5.78**	-4.76**
	(0.78)	(0.40)	(0.44)	(0.48)
x ln(PPP Intensity$_b$)	-3.75**	-2.40**	-1.32**	-1.10*
	(0.65)	(0.56)	(0.46)	(0.44)
Local Branch$_{i,b}$	2.04**	-1.13**	-1.40*	-1.13*
	(0.58)	(0.25)	(0.63)	(0.52)
x ln(PPP Intensity$_b$)	-5.00**	-0.22	-1.17	-0.60
	(0.51)	(0.30)	(0.72)	(0.42)
x Relationship$_{i,b}$	2.09**	1.24**	2.67**	1.63**
	(0.66)	(0.22)	(0.60)	(0.54)
ln(PPP Intensity$_b$)	1.77**		0.06	
	(0.56)		(0.34)	
R^2	0.206	0.290	0.330	0.431
Obs.	117,487	116,950	117,487	116,950
Controls?	X	X	X	X
County FE	X	X	X	X
Lending Bank FE?		X		X
Weighted			X	X
Relationship Benefit (days)	3.7 - 11.2	3.1 - 7.9	5.8 - 8.4	4.8 - 6.9

Notes: This table presents estimates from regressing the number of days until origination on log PPP intensity of the lending bank, an indicator for whether the lending bank has a branch within 2 miles of the borrower, an indicator for whether the lending bank previously provided an SBA loan to the borrower, as well as all pairwise interactions of these variables. The sample covers bank PPP loans to borrowers that previously took out an SBA loan. Columns 2 and 4 additionally include lending bank fixed effects, and columns 3 and 4 weight by the inverse of the number of loans in the sample by the lending bank. All specifications control for the size of the loan, whether the business has fewer than 5 employees and tract characteristics (an urban indicator, the share of employees that are nonwhite, and the logarithms of prepandemic small business lending and employment). Standards errors, in parentheses, are clustered by bank. $^{+}$,*,** indicate significance at 10%, 5% and 1%, respectively. The bottom row reports the range of the benefits of borrowing from a relationship bank for banks with an ln(PPP Intensity) between 0 and 2 (assuming a nonlocal bank).

6 Tract level effects

The results thus far indicate that borrowers are typically close to their relationship banks and get credit earlier if that relationship bank is a high-intensity PPP lender. Now I investigate the implications of these facts for geographic differences in credit availability. First, I show that a higher average PPP intensity for banks with branches within 2 miles of a tract is associated with a smaller delays in receiving PPP loans and fewer borrowers switching to fintechs or distant banks. Second, I show that these effects decay quickly as distance increases.

6.1 Effects of PPP Intensity Within 2 Miles

Table 4 regresses tract level PPP outcomes on the average ln(PPP intensity) for the branches within 2 miles of a census tract, weighted by branch deposits. PPP intensity here is calculated as the ratio of a bank's PPP lending *in other tracts* to prepandemic small business lending in order to avoid reverse causality from strong PPP lending in a particular tract causing local banks to have a high PPP intensity.[27] I additionally include controls for prepandemic tract small business lending and the number of branches within two miles of the tract to account for the likely availability of relationship lenders. I include the logarithm of small business employment and variables pertaining to earnings for local workers to account for the amount of PPP credit firms were eligible for (which was tied to small firms' payrolls).[28] Odd columns present OLS estimates of how the PPP intensity of local banks affects lending outcomes, while even columns present results weighting by tract small business employment.

[27] Additionally, Appendix Table A3 presents similar estimates, but measuring local supply conditions with the share of deposits in nearby branches that are from the top 4 banks. Given the geographic extent of these banks' operations, there is less concern about reverse causality for this supply measure.

[28] The PPP program essentially provided credit for up to 2.5 times monthly payroll for businesses with 500 or fewer employees. 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 × Average Monthly Payroll of Eligible Firms) and iii. ln(Share of Eligible Payroll Funded). I control 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. Effects of other variables can thus be more reasonably attributed to bank supply conditions.

All specifications include county fixed effects.

In the first two columns, the dependent variable is the average number of days to origination for PPP loans in a census tract. A unit increase in the average ln(PPP intensity) of local banks reduces the average time to origination by roughly 1 day. This elasticity is in the range of effects found in the loan level data.[29]

In columns 3 and 4, the dependent variable is the share of credit from banks with nearby branches. A unit increase in the average ln(PPP Intensity) of nearby branches increases the market share of nearby banks by roughly 4 percentage points. Roughly 15% of this effect is accounted for by a lower market share for fintech lenders, as shown by columns 5 and 6.[30] The rest reflects a decline by further-off banks or other nonbank lenders (not shown).

In the last two columns, the dependent variable is the logarithm of total PPP lending. While the activity of local banks significantly affects the timing of loan receipt and the composition of who does the lending, it appears to have little affect on loan volumes. A unit increase in the average ln(PPP intensity) only increases expected loan volumes by 1 or 2 percent, and is insignificant in the weighted specification.

Regarding estimates for the other variables, 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 about 4 day delay in receiving credit, on average. This result is consistent with other work presenting evidence of racial discrimination in the allocation of PPP credit (Howell et al., 2021; Chernenko and Scharfstein, 2022). However, this result could also indicative of minority-owned firms being less likely to have bank relationships (Mills and Battisto, 2020), resulting in less credit availability controlling for local supply conditions.[31] Indeed, the lower

[29]In Appendix Table A1, the coefficient on the interaction between ln(PPP Intensity)$_b$ and Local Branch$_{i,b}$ is -2.5 in the unweighted specification and -0.6 in the weighted specification.

[30]The fintech share is the share of loans made by the following lenders: Celtic Bank, Cross River Bank, Intuit, Fundbox, Kabbage, Readycap and WebBank. This includes both nonbanks, and some prominent banks with significant lending through fintech partnerships. Fintechs make up about a quarter of the decline in market share of local banks when market shares are measured by counts rather that volumes, as they tended to originate smaller loans.

[31]While the SBA collected data on the race of borrowers, that field is rarely populated. Consequently

Table 4: Tract Level Origination Speed

	Days to Origination		Local Bank Share (pp)		Fintech Share (pp)		ln(PPP Lending)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(PPP Intensity)$_j$	-1.17**	-1.02**	4.03**	4.71**	-0.70**	-0.56**	0.02*	0.01
	(0.20)	(0.16)	(0.34)	(0.36)	(0.18)	(0.10)	(0.01)	(0.01)
ln(Branches)$_j$	-0.81**	-0.54**	14.73**	14.87**	-0.46**	-0.27**	0.00	0.00
	(0.12)	(0.07)	(0.28)	(0.28)	(0.10)	(0.05)	(0.00)	(0.00)
ln(SB Lending)$_j$	-0.30**	0.03	-0.56**	0.13	0.22**	0.41**	0.17**	0.16**
	(0.10)	(0.07)	(0.17)	(0.20)	(0.08)	(0.06)	(0.01)	(0.01)
Nonwhite$_j$	23.61**	20.75**	-13.00**	-9.92**	18.13**	9.83**	-0.08	-0.43**
	(2.41)	(2.19)	(2.03)	(2.28)	(2.87)	(1.75)	(0.09)	(0.06)
ln(SB Emp)$_j$	-3.87**	-3.33**	1.45**	0.43^+	-4.04**	-1.98**	0.87**	0.94**
	(0.12)	(0.09)	(0.21)	(0.25)	(0.26)	(0.12)	(0.01)	(0.01)
Earnings > \$3333$_j$	-0.02	-0.84	-9.34**	-15.20**	0.52	-1.61*	0.46**	0.39**
	(0.77)	(0.84)	(1.81)	(1.89)	(1.04)	(0.72)	(0.08)	(0.06)
Earnings < \$1250$_j$	1.85^+	4.25**	4.44*	1.51	5.10**	4.26**	-0.82**	-0.89**
	(1.11)	(1.05)	(1.92)	(2.11)	(1.15)	(0.77)	(0.10)	(0.07)
College$_j$	-8.61**	-1.50	21.61**	25.88**	-4.00**	0.56	0.35**	0.03
	(1.38)	(1.20)	(2.37)	(2.61)	(1.48)	(0.78)	(0.11)	(0.11)
R^2	0.645	0.678	0.407	0.519	0.397	0.344	0.822	0.909
Obs.	48,897	48,897	48,301	48,301	46,226	46,226	48,897	48,897
County FE?	X	X	X	X	X	X	X	X
Employment Weighted?		X		X		X		X

Notes: This table presents estimates from the equation:

$$y_j = \alpha_{c(j)} + \beta \ln(\text{PPP Intensity})_j + \gamma' X_j + \varepsilon_j$$

where y_j is a PPP outcome for a tract j. ln(PPP Intensity)$_j$ is the average of the logarithm of the ratio of PPP lending in other tracts to prepandemic small business lending for banks with branches within 2 miles of the tract centroid, weighted by the deposits in those branches. 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; 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. $\alpha_{c(j)}$ is a county fixed effect. y_j is the average number of days until origination for the loans in the tract in columns 1 & 2, the percent of credit provided by banks within two miles in columns 3 & 4, the percent of credit provided by fintech lenders in columns 5 & 6 and the logarithm of 2020 total PPP lending in the tract in columns 7 & 8. 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.

market share of local banks in tracts with higher minority employment is consistent with relationship loans being less available in these tracts. However, it is unclear the extent to which this result reflects a lack of relationships, or a lack of credit from the relationships that do exist.[32]

Additionally, census tracts with more branches within 2 miles, more college educated employees, or more small business employment are able to receive credit sooner, have a higher share of PPP lending accounted for by nearby banks, and have a lower share of credit accounted for by fintechs. Variation in the volume of PPP lending is mostly accounted for by the amount of small business employment, and variables relating to local earnings, as would be expected given that PPP amounts were tied to business payrolls.

Overall, the results show that when local banks are less active in PPP, borrowers turn to other lenders for loans. This switching appears to be costly, as borrowers receive loans later on average. Although low-intensity banks provide less credit to the tract than other banks would, the ultimate effect on PPP loan volumes is relatively modest. 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 program—when unemployment was at its peak—may have limited its effectiveness (Doniger and Kay, 2023).

6.2 Effects of PPP Intensity by Distance

Table 4 showed that the PPP intensity of banks within 2 miles of a tract is important in determining how quickly borrowers can access credit. Now I investigate whether this is the appropriate distance to consider, or whether the activity of more distant banks matters as well.

it is only feasible to analyze results based on the racial composition of the local workforce instead of the demographics of the owners themselves.

[32] The effect of racial composition on loan volumes is unclear. One specification shows notable effects for the nonwhite share and the other notable effects for the college share. 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).

Figure 7 presents estimates of $\{\beta_d\}$ from the equation:

$$y_j = \alpha_{c(j)} + \sum_d \beta_d \ln(\text{PPP Intensity})(d)_j + \gamma' X_j + \varepsilon_j$$

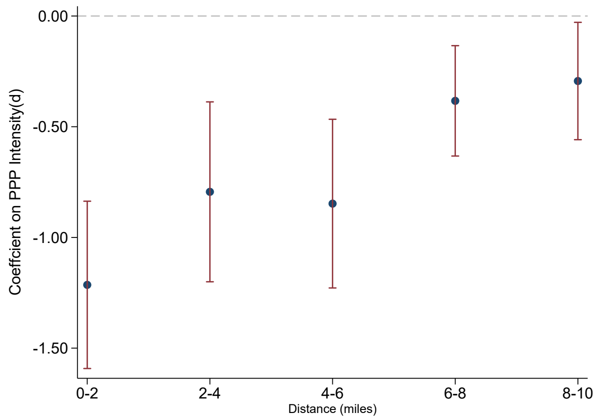
where $\ln(\text{PPP Intensity})(d)_j$ is the deposit weighted average ln(PPP intensity) of banks with branches between $d-2$ and d miles from tract j. y_j is one of the previously discussed tract level PPP outcomes: the average number of days until origination (Panel 7a), the share of loans from banks with nearby branches (Panel 7b), the share of loans from fintechs (Panel 7c) or the logarithm of PPP loan volume (Panel 7d).[33]

In each panel, the coefficient on $\ln(\text{PPP Intensity})(2)_j$ is similar to the corresponding estimate in Table 4, meaning that the controls for PPP intensity at more distant banks does not affect the estimated effects for banks within 2 miles. The effects then decline towards 0 as distance rises (with the sign reversing at greater distances when total loan volumes are the dependent variable). The effects of PPP intensity on the average number of days to origination are the slowest to decay with distance. However, even there, the PPP intensity of banks within 2 miles affects origination timing about 50 percent more than for banks 2–6 miles away, and about 3 times as much as for banks 6–10 miles away. For the fintech market share, the PPP intensity within 2 miles matters about twice as much as for banks 2–4 miles away. For the market share of local banks or total PPP lending, effects either go to zero or reverse sign for banks 2–4 miles away. In short, the effects of PPP intensity on the timing or composition of tract lending are predominantly driven by banks within 2 miles.

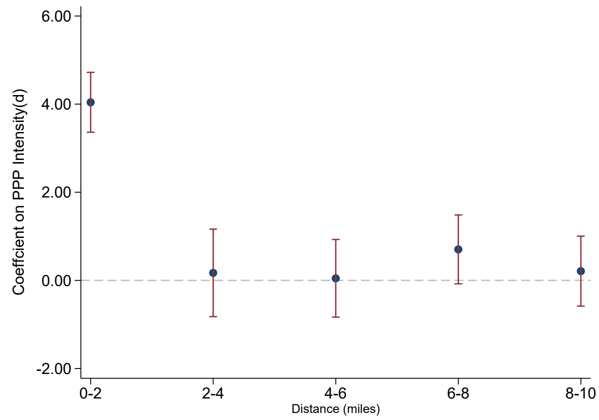
Overall, these results show that variation in supply conditions have very localized effects. These effects are unlikely to be driven by bank preferences for nearby borrowers as loan guarantees remove the benefits of local information or easier monitoring. Likewise, these effects are unlikely to be driven by borrower preferences for nearby banks, as transit costs

[33] X_j is as in Table 4, but with additional dummy variables indicating whether there are no banks within a particular distance band. To maintain the same sample as in the previous analysis, ln(PPP intensity) is recoded to 0 when there are no banks within a band and tracts are dropped if there are no banks within 2 miles.

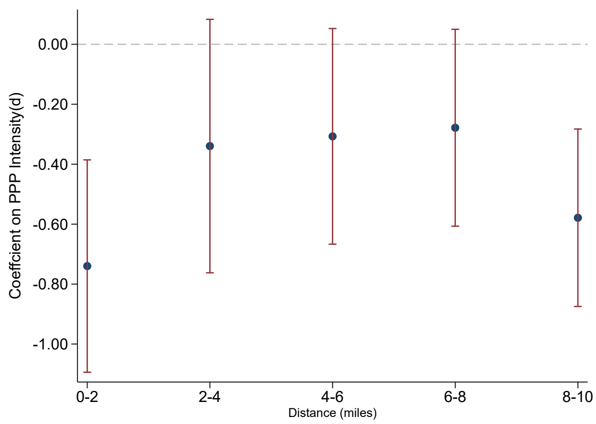
Figure 7: Effects of PPP Intensity by Bank Distance



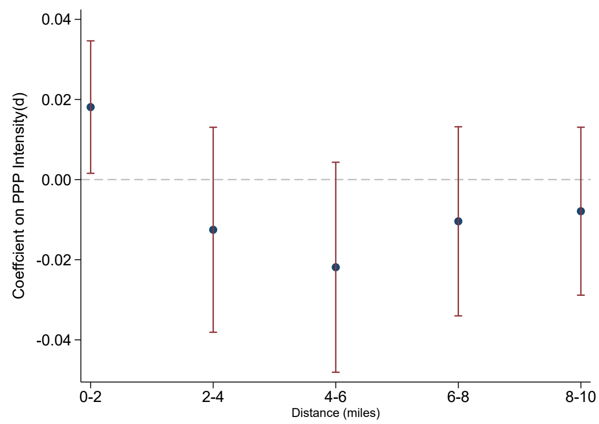
(a) Days Until Origination



(b) Local Bank Share



(c) Fintech Share



(d) ln(PPP Lending)

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

$$y_j = \alpha_{c(j)} + \sum_d \beta_d \ln(\text{PPP Intensity})(d)_j + \gamma' X_j + \varepsilon_j$$

where $\ln(\text{PPP Intensity})(d)_j$ is the deposit weighted average ln(PPP intensity) for branches between $d-2$ and d miles from a census tract. y_j is a PPP outcome for tract j: the average number of days between the start of PPP and the approval date (panel a), the share of lending by nearby banks (panel b), the share of lending by fintechs (panel c), and the natural logarithm of the value of PPP approvals (panel d). 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; 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. $\ln(\text{PPP Intensity})(\text{d})_j$ is recoded to 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.

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 in switching from relationship lenders driving the results.

7 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 go to borrowers within 2 miles of a branch. Borrowers receive loans sooner if they get credit from a nearby bank, especially if that bank is a more active PPP lender. Borrowers where nearby banks are less active in PPP switch to fintechs or other distant lenders, resulting in delays receiving credit. When I estimate a model to match the observed relationships between distance, PPP intensity, and origination timing, I find that relationship borrowers were able to receive credit 5 to 9 days earlier than other borrowers from the same bank. Analysis of a subsample of PPP loans to previous SBA 7(a) borrowers produces a similar range of benefits to relationship borrowing.

Overall, the findings demonstrate the importance of bank relationships for prompt access to credit. Though increased lending from distant lenders counteracted declines in areas where local banks were less active, there were material delays involved. As such delays have been shown to be associated with worse job losses (Doniger and Kay, 2023), the results suggest that intermediation frictions likely reduced the program's effectiveness. Furthermore, these findings highlight a cost to intermediating aid through the banking sector; if firms without banking relationships are more financially constrained, funding dispersed by banks is less likely to flow to where it is most needed.

References

Agarwal, S. and R. Hauswald (2010). Distance and private information in lending. *The Review of Financial Studies 23*(7), 2757–2788.

Amiram, D. and D. Rabetti (2020). The relevance of relationship lending in times of crisis. *Available at SSRN 3701587*.

Bartik, A. W., M. Bertrand, F. Lin, J. Rothstein, and M. Unrath (2020). Measuring the labor market at the onset of the COVID-19 crisis. Technical report, National Bureau of Economic Research.

Bartik, A. W., Z. B. Cullen, E. L. Glaeser, M. Luca, C. T. Stanton, and A. Sunderam (2020). The targeting and impact of Paycheck Protection Program loans to small businesses. Technical report, National Bureau of Economic Research.

Brevoort, K. P. and J. D. Wolken (2009). Does distance matter in banking? In *The changing geography of banking and finance*, pp. 27–56. Springer.

Cattaneo, M. D., R. K. Crump, M. H. Farrell, and Y. Feng (2019). On binscatter. *arXiv preprint arXiv:1902.09608*.

Chernenko, S. and D. S. Scharfstein (2022). Racial disparities in the paycheck protection program. Technical report, National Bureau of Economic Research.

Degryse, H. and S. Ongena (2005). Distance, lending relationships, and competition. *The Journal of Finance 60*(1), 231–266.

Denes, M., S. Lagaras, and M. Tsoutsoura (2021). First come, first served: The timing of government support and its impact on firms. Technical report.

Di, W. and N. Pattison (2020). Distant lending, specialization, and access to credit.

Doniger, C. L. and B. Kay (2023). Long-lived employment effects of delays in emergency financing for small businesses. *Journal of Monetary Economics 140*, 78–91.

Duchin, R., X. Martin, R. Michaely, and H. Wang (2022). Concierge treatment from banks: Evidence from the paycheck protection program. *Journal of Corporate Finance 72*, 102124.

Erel, I. and J. Liebersohn (2020). Does fintech substitute for banks? Evidence from the Paycheck Protection Program. Technical report, National Bureau of Economic Research.

Faulkender, M. W., R. Jackman, and S. Miran (2023). The job preservation effects of paycheck protection program loans. *Available at SSRN 3767509*.

Granja, J., C. Makridis, C. Yannelis, and E. Zwick (2022). Did the Paycheck Protection Program hit the target? *Journal of financial economics 145*(3), 725–761.

Howell, S. T., T. Kuchler, D. Snitkof, J. Stroebel, and J. Wong (2021). Automation and racial disparities in small business lending: Evidence from the Paycheck Protection Program. Technical report, Working paper 29364. National Bureau of Economic Research.

Humphries, J. E., C. A. Neilson, and G. Ulyssea (2020). Information frictions and access to the Paycheck Protection Program. *Journal of public economics 190*, 104244.

Joaquim, G. and F. Netto (2020). Bank incentives and the impact of the Paycheck Protection Program. *Available at SSRN 3704518*.

Kurmann, A., E. Lalé, and L. Ta (2022). Measuring small business dynamics and employment with private-sector real-time data.

Li, L. and P. E. Strahan (2021). Who supplies PPP loans (and does it matter)? Banks, relationships, and the COVID crisis. *Journal of Financial and Quantitative Analysis 56*(7), 2411–2438.

Merker, V., T. Ling, and D. Tannebaum (2020). PPP is a complience minefield for banks. *American Banker*.

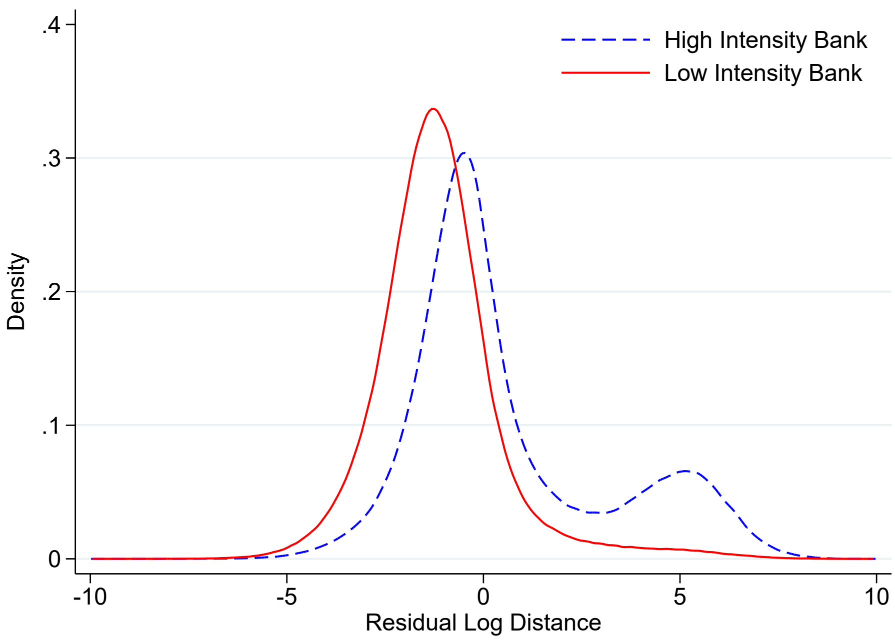
Mills, C. K. and J. Battisto (2020). Double jeopardy: COVID-19s concentrated health and wealth effects in black communities. *Federal Reserve Bank of New York*.

Pogach, J. and M. J. Kutzbach (2022). Bank technology and the covid-19 pandemic. *FDIC Center for Financial Research Paper* (2022-02).

A Appendix

A.1 Figures

Figure A1: Residualized Distance by Bank PPP Intensity



Notes: This chart plots kernel density estimates of the logarithm of the distance to the lending bank, residualizing on log loan amount, a small firm indicator, and tract fixed effects. The blue line shows the distribution for banks with a PPP intensity above 1, and the red line the distribution for those below 1.

A.2 Tables

Table A1: Bank Proximity and Origination Speed

	Days to Origination					
	(1)	(2)	(3)	(4)	(5)	(6)
ln(PPP Intensity$_b$)	-2.41**	-1.62	-0.65	-1.17**	-1.19**	-1.00**
	(0.75)	(1.10)	(1.19)	(0.18)	(0.18)	(0.20)
ln(PPP Intensity$_b$)^2	1.30**	1.12**	1.01**	0.61**	0.60**	0.59**
	(0.14)	(0.13)	(0.13)	(0.09)	(0.09)	(0.09)
Local Branch$_{i,b}$	-0.87$^+$	-1.11*	-0.39	-1.35**	-1.35**	-1.29**
	(0.47)	(0.52)	(0.45)	(0.11)	(0.11)	(0.11)
x ln(PPP Intensity$_b$)			-2.49**			-0.63**
			(0.89)			(0.18)
ln(Loan Amount)$_{i,b}$	-4.19**	-4.07**	-4.04**	-4.64**	-4.63**	-4.63**
	(0.34)	(0.36)	(0.35)	(0.05)	(0.05)	(0.05)
Small Firm$_{i,b}$	4.43**	4.46**	4.47**	4.09**	4.09**	4.10**
	(0.78)	(0.78)	(0.78)	(0.12)	(0.12)	(0.12)
Internet Bank$_b$		2.69	1.14		12.24**	11.60**
		(4.11)	(4.33)		(3.64)	(3.56)
Top 4$_b$		4.24*	3.47$^+$		4.58*	4.28*
		(1.90)	(1.91)		(1.94)	(1.97)
R^2	0.265	0.267	0.268	0.182	0.182	0.182
Obs.	4,077,112	4,077,112	4,077,112	4,077,112	4,077,112	4,077,112
Tract Controls?	X	X	X	X	X	X
County FE?	X	X	X	X	X	X
3-Digit NAICS FE?	X	X	X	X	X	X
Weighted?				X	X	X

Notes: This table presents estimates from regressing the number of days until origination on log PPP intensity of the lending bank, log PPP intensity squared and an indicator for whether the bank has a branch within 2 miles of the borrower. Specifications in columns 2 & 5 add controls for whether the bank is one of the four largest lenders or an internet bank, and the specifications in columns 3 & 6 add an interaction of log PPP intensity with the local lender dummy. All specifications control for the size of the loan, whether the business has fewer than 5 employees and tract characteristics (nonwhite employment share, log small business employment, log prepandemic small business lending, and an urban indicator), and include county and 3-digit NAICS fixed effects. Estimates for tract controls are not displayed. Standards errors, in parentheses, are clustered by county. $^{+}$,*,** indicate significance at 10%, 5% and 1%, respectively.

Table A2: Bank Proximity and Round 1 Funding

	Round 1 Indicator×100					
	(1)	(2)	(3)	(4)	(5)	(6)
ln(PPP Intensity$_b$)	7.86**	4.33**	2.52	3.63**	3.62**	3.30**
	(2.00)	(1.62)	(1.81)	(0.29)	(0.29)	(0.30)
ln(PPP Intensity$_b$)^2	-1.82**	-0.70**	-0.50*	-1.22**	-1.21**	-1.20**
	(0.35)	(0.21)	(0.22)	(0.12)	(0.12)	(0.12)
Local Branch$_{i,b}$	1.15	2.14*	0.79	2.53**	2.56**	2.45**
	(1.19)	(0.88)	(0.82)	(0.23)	(0.23)	(0.23)
x ln(PPP Intensity$_b$)			4.64**			1.07**
			(1.47)			(0.30)
ln(Loan Amount)$_{i,b}$	9.95**	9.17**	9.13**	10.79**	10.78**	10.79**
	(0.52)	(0.68)	(0.68)	(0.09)	(0.09)	(0.09)
Small Firm$_{i,b}$	-5.46**	-5.63**	-5.64**	-10.03**	-10.03**	-10.04**
	(0.91)	(0.84)	(0.85)	(0.26)	(0.26)	(0.26)
Internet Bank$_b$		-22.82**	-19.94**		-9.67	-8.59
		(5.85)	(5.98)		(6.15)	(6.36)
Top 4$_b$		-21.71**	-20.28**		-16.32**	-15.81**
		(3.04)	(3.14)		(5.91)	(5.99)
R^2	0.259	0.283	0.285	0.226	0.226	0.226
Obs.	4,077,112	4,077,112	4,077,112	4,077,112	4,077,112	4,077,112
Tract Controls?	X	X	X	X	X	X
County FE?	X	X	X	X	X	X
3-Digit NAICS FE?	X	X	X	X	X	X
Weighted?				X	X	X

Notes: This table presents estimates from regressing an indicator for whether a loan was originated during the first round of PPP funding on log PPP intensity of the lending bank, log PPP intensity squared and an an indicator for whether the bank has a branch within 2 miles of the borrower. 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. Specifications in columns 2 & 5 add controls for whether the bank is one of the four largest lenders or an internet bank, and the specifications in columns 3 & 6 add an interaction of log PPP intensity with the local lender dummy. All specifications control for the size of the loan, whether the business has fewer than 5 employees and tract characteristics (nonwhite employment share, log small business employment, log prepandemic small business lending, and an urban indicator), and include county and 3-digit NAICS fixed effects. Estimates for tract controls are not displayed. Standards errors, in parentheses, are clustered by county. $^{+}$,*,** indicate significance at 10%, 5% and 1%, respectively.

Table A3: Tract Level Origination Speed

	Days to Origination		Local Bank Share (pp)		Fintech Share (pp)		ln(PPP Lending)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Top 4 Share$_j$	2.27**	1.86**	-4.86**	-7.06**	1.84**	1.11**	-0.04**	-0.02
	(0.39)	(0.37)	(0.77)	(0.74)	(0.39)	(0.24)	(0.02)	(0.01)
ln(Branches)$_j$	-0.82**	-0.53**	14.72**	14.85**	-0.47**	-0.27**	0.00	0.00
	(0.12)	(0.07)	(0.29)	(0.29)	(0.11)	(0.05)	(0.00)	(0.00)
ln(SB Lending)$_j$	-0.30**	0.03	-0.55**	0.14	0.22**	0.41**	0.17**	0.16**
	(0.10)	(0.07)	(0.17)	(0.20)	(0.08)	(0.06)	(0.01)	(0.01)
Nonwhite$_j$	23.60**	20.79**	-13.26**	-10.25**	18.07**	9.85**	-0.08	-0.43**
	(2.46)	(2.18)	(2.09)	(2.28)	(2.89)	(1.75)	(0.09)	(0.06)
ln(SB Emp)$_j$	-3.86**	-3.31**	1.44**	0.38	-4.03**	-1.97**	0.87**	0.94**
	(0.12)	(0.09)	(0.21)	(0.25)	(0.26)	(0.12)	(0.01)	(0.01)
Earnings > \$3333$_j$	0.02	-0.80	-9.40**	-15.36**	0.55	-1.60*	0.46**	0.39**
	(0.78)	(0.85)	(1.84)	(1.96)	(1.05)	(0.74)	(0.08)	(0.06)
Earnings < \$1250$_j$	1.81^{+}	4.21**	4.49*	1.58	5.06**	4.23**	-0.82**	-0.89**
	(1.07)	(1.02)	(1.96)	(2.19)	(1.15)	(0.77)	(0.10)	(0.07)
College$_j$	-8.69**	-1.57	21.75**	26.10**	-4.08**	0.52	0.35**	0.03
	(1.38)	(1.20)	(2.44)	(2.62)	(1.47)	(0.78)	(0.11)	(0.11)
R^2	0.645	0.678	0.405	0.517	0.397	0.344	0.822	0.909
Obs.	48,902	48,902	48,306	48,306	46,231	46,231	48,902	48,902
County FE?	X	X	X	X	X	X	X	X
Employment Weighted?		X		X		X		X

Notes: This table presents estimates from the equation:

$$y_j = \alpha_{c(j)} + \beta \text{Top 4 share}_j + \gamma' X_j + \varepsilon_j$$

where y_j is a PPP outcome for a tract j. Top 4 share$_j$ 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; 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. $\alpha_{c(j)}$ is a county fixed effect. y_j is the average number of days until origination for the loans in the tract in columns 1 & 2, the percent of loans originated by banks within two miles in columns 3 & 4, the percent of loans originated by fintech lenders in columns 5 & 6, and the logarithm of 2020 PPP lending in the tract in columns 7 & 8. 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.