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Can Bank Density Provide Insights on the Appropriation of Disaster Relief Funds? Evidence from the Paycheck Protection Program*

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Abstract: In response to the COVID-19 pandemic, Congress in conjunction with the Small Business Administration (SBA) created the Paycheck Protection Program (PPP) to help small business owners retain employees. We improve on previous literature exploring the relationship between bank density and PPP loan dispersion by implementing precisely geocoded data to map loans to commuting zones. Revisiting results in Deming and Weiler (2023), we confirm the statistically significant relationship between bank density and PPP loans per small business. We consider three distinct periods of lending to analyze how changes in the PPP loan program rules might have impacted dispersion. The coefficient in the regression of loans per small business on bank density is largest in the final wave of lending, and in commuting zones with high loan densities. This suggests that having additional bank branches in the commuting zone may have helped facilitate rapid dispersion of relief funds to high demand areas during the program.

Keywords: banking; relationship lending; geography; CARES Act; regional

JEL Codes: H25, R12, R51

1. INTRODUCTION

The COVID-19 pandemic created the first official economic downturn since the Great Recession. In response, Congress created the Paycheck Protection Program (PPP) to help

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small business owners retain employees during periods of reduced mobility and sales. The PPP loans program allowed small business to obtain low-interest loans to cover payroll and other expenses, while eliminating liability for the loan originators, existing Small Business Administration (SBA) 7(a) lenders.

On March 27, 2020, Congress signed the CARES act into law, allocating $349 billion for the PPP program. Applications opened on April 3rd of that year, and the following day for independent contractors and self employed individuals. Within less than two weeks, the inital allocation of funding had been tapped out leading to a temporary lull in the program. On April 24th, Congress approved an additional $310 billion for the program with a deadline date of June 30, ultimately extended to August 8. At the August deadline, over $130 billion of allocated funds remained unclaimed and, after a hiatus in Fall 2020, Congress again extended the program, with additional funding resuming in January 2021. By the conclusion of the program in late May 2021, nearly $800 billion in funding had been disbursed as PPP loans under the CARES act program.

The Paycheck Protection Program has already prompted extensive literature covering optimal allocation theory (Joaquim and Netto, 2022), bank performance (Granja et al., 2022), flows to minority communities (Fairlie and Fossen, 2022), business survival (Bartik et al., 2020), the impact on employment, e.g., Joaquim and Netto (2020) and Kapinos (2021) and on GDP (Autor et al., 2022). Yet the question of local banking relationships and access to the PPP program funding is particularly important for this business support policy. Margins on PPP loans were very small (Marsh et al., 2020). Banks thus had extra incentive to rely on soft information about the borrower, which is more transparent in the presence of local banking relationships.

Banking services vary regionally, creating potential inequality in the ability to access credit. While many banking services can be transacted remotely via banking and a rising fintech sector, there are still public and personal benefits derived from proximity to a bank branch or headquarters (Deming and Weiler, 2023). Local banks are able to utilize relationship lending, based on soft information gleaned through business or personal networks for credit decisions, e.g., Petach et al. (2021) and Berger et al. (2022). For certain borrowers, such as those located in rural areas or banking deserts within urban areas, this soft information is opaque, generating a potential for imbalance in borrowing opportunity based solely on geography, e.g., Akerlof (1970), Bunten et al. (2015), and Conroy et al. (2017). While the notion of banking deserts is anecdotally rich, there are few independent empirical analyses of the extent of the geographically based banking access problem. Previous literature suggests that the inequality is most pronounced between urban and rural areas because the travel time from rural areas to banking locations is often much longer than in urban areas, e.g., Kashian et al. (2015) and Morgan et al. (2018).

A few recent publications address the geospatial relationship between banking access and relationship-based lending. Firms which receive PPP loans from lenders with whom they have had a past relationship receive larger loans and more quickly (Rabetti, 2022), while firms with personal ties to banks are more likely overall to receive PPP loans (Duchin et al., 2022). Smaller community banks responded more quickly to PPP loan requests and lent more intensively to small businesses than larger banks (James et al., 2021). Because small firms usually must depend on financial intermediaries such as commercial banks to obtain credit , relationship lending or the geospatial lack theoreof may be particularly important for small businesses. Small businesses were particularly fragile during the COVID-19 crisis (Bartik et al., 2020), meaning that for many, firm survival could have depended on access to PPP funds. Borrowers located geographically near more active PPP lenders received credit earlier (Glancy, 2021), suggesting a potential geographic inequality in access to PPP funds.

Previous literature addresses this potential inequality in access to important banking programs. Relationship lending has the potential to enhance disadvantageous or discriminatory banking practices. Smaller businesses in general had lower awareness of government programs during COVID-19, were less likely to apply for PPP funding, and were less likely to report having their application approved (Humphries et al., 2020). PPP funding flowed less rapidly to minority communities (Fairlie and Fossen, 2022). Black-owned businesses were less likely to receive PPP loans (Chernenko and Scharfstein, 2022) and received loans that were smaller than White-owned businesses. This effect is marginally smaller in areas with more bank competition and disappears in the later stages of PPP which allowed for entry by fintechs and other non-traditional lenders (Atkins et al., 2022). Together, these results suggest that further research is warranted into the geographic relationship between banking locations and the dispersion of PPP loans. Because data on PPP loans were released with geographic information at the ZIP code level, previous research has commonly approximated loans from ZIP code to county. A small number of more recent papers have used GIS programs to geocode the addresses found in the PPP loan dataset to levels of analysis which coincide more favorably with publicly available data, e.g., Borawski and Schweitzer (2021) and Glancy (2021).

This paper makes three main contributions to the literature. First, we revisit previous results from Deming and Weiler (2023) which find a significant positive relationship between the density of banking locations and PPP loans, with the geocoded data update. In doing so, we confirm the significant and positive relationship between bank density and PPP loans per small business. Second, we extend upon previous literature by considering loans issued over the entirety of the PPP program, and decomposing those loans into three distinct lending periods based on a timeline of actions taken by the SBA. We find that while there is a significant and positive relationship between bank and loan density across all loan periods, this relationship is strongest in the final lending period. Third, this paper is novel in considering the possibility that competitive pressures associated with bank location and the origination fee structure of the loan program could have played a part in explaining geographic patterns of high loan density. We show that the relationship between bank and loan density is the most intense in commuting zones which received the largest number of loans per small business. In light of literature suggesting that smaller banks originated larger than expected shares of the loans, we suggest that loan origination fee structure might have driven this trend in areas with high bank density, and therefore high competition.

The remainder of the paper is divided into the following sections: Section 2 describes our data sources and how the data was matched to the appropriate geographical areas. Section 3 presents our findings on the relationship between bank density and PPP loan dispersion. Within this section, we study 1) loans and loan amounts per small business, 2) changes in lending patterns over time and 3) interquantile changes in the intensity of the relationship between bank and loan density. Section 4 concludes.

2. DATA

Data on Paycheck Protection Program loans come from the Small Business Administration (SBA) and were coded into Census Blocks, Tracts, Counties, and States by Geocodio and made public by Glancy (2021). These data contain information on all individual loans distributed through the PPP from the first phase in April of 2020 until the official end of the program on May 31, 2021. For each loan, the date of approval, loan amount, business address, reported number of jobs, and demographic characteristics of the business owner are observed. However a large number of loans are missing information from the demographic survey.

PPP loan data is analyzed in three waves, the first spanning from the introduction of the program to the initial exhaustion of the funds on April 16, a second wave from the restart of the program to the initial revised deadline of August 8, 2020, and a final wave spanning to the end of the program. Analysis of the different waves of the PPP loan program will allow for discussion of whether changes to the program, such as allowing fintechs and other non-traditional lenders to originate the loans in the third wave, impacted the dispersion of PPP loans.

Commuting Zones (CZs), first developed by Tolbert and Sizer (1996), and designated by the U.S. Department of Agriculture Economic Research Service (ERS)[1] are the primary units of analysis. CZs offer two main advantages over other geographic delineations. First CZs represent local economies better than other political boundaries by grouping counties together which have strong commuting ties. Second, CZs contiguously cover the continental United States meaning that all businesses which received a PPP loan will be retained in the sample. Commuting Zones also lend themselves particularly well to studying the distribution of PPP loans because small businesses (especially rural) may have to seek banking services outside of their city or county due to a lack of banking access (Deming and Weiler, 2023). Using Commuting Zones as the focal unit of analysis will more accurately capture the number of banks available to small businesses. PPP loan data at the Census County level is aggregated to Commuting Zones by matching the geocoded county of business location to a crosswalk provided by the ERS.

Commuting zones are geographically diverse and do not have identical populations or economies. For this reason, we normalize our outcomes of interest by the number of small businesses in each CZ. We focus on the number of small businesses in each CZ since the Paycheck Protection Program was designed to provide economic relief for small businesses. The Small Business Administration definition of a small business varies by industry, so when normalizing covariates by the number of small businesses, we utilize a more general definition of a small business adopted by the Small Business Administration — a business with fewer than 500 employees. To get the number of businesses with fewer than 500 employees, we use data from the most recent County Business Patterns from the U.S. Census Bureau, aggregated to the Commuting Zone level. Previous literature approximates loan data into Commuting Zones based on ZIP code weighting. The geocoded PPP data allows for more precise analysis of loan dispersion. We find, in a comparison between the ZIP code weighted

[1]2000 designations

and precisely geocoded datasets, that the two are highly correlated. Weighting is a potentially reasonable approach to converting ZIP code data to Commuting Zone level. However, the precisely geocoded data does eliminate some zeros in the approximated data which were likely erroneous. As a result, the implementation of GIS procedures to improve the accuracy of geospatial estimation is an important addition to the literature on banking and PPP loans.

Our main source of commuting zone-level economic characteristics, such as population, household income, demographic characteristics, level of education, and land area, is from the American Community Survey 5-year estimates for 2015-2019. This source provides data on these characteristics at the county level which are then aggregated up to the CZ level. Data on county GDP comes from the Bureau of Economic Analysis Regional Economic Accounts and summed up to CZ GDP. These data are for 2019 since that is the most recent data available at the county level, and effectively set the stage for the 2020 pandemic that followed. Following Liu and Volker (2020), data on the number of COVID-19 cases comes from The New York Times which continuously tracked the number of daily COVID-19 cases by county from the beginning of the pandemic. To accurately measure the impact of COVID-19 cases and potential local lock-down measures in an area, we use the cumulative count COVID-19 cases for each county on April 3, 2020, which is when the program opened for small businesses. The county case count is then aggregated up to the commuting zone. We get our data for labor market outcomes from the Bureau of Labor Statistics' (BLS) Local Area Unemployment Statistics. Since the BLS measures employment in first two weeks of the month, we use the county data on employment from April 2020 since these data reflect the reality of local labor markets when business establishments were deciding whether to apply for a PPP loan.

We obtain our data on bank location from two sources: Federal Deposit Insurance Corporation (FDIC) and the National Credit Union Administration (NCUA). We focus on both banks and credit unions because both were authorized to provide PPP loans to small businesses. We obtain the location of all bank branches and headquarters from the FDIC's Institutions and Locations database. This provides the addresses of all federally insured banks, county of banks location, the service type of banks, and whether the bank is the main office or a branch location. We create a measure of total banks by including all full-service banks, both brick and mortar and retail locations, as well as permanent limited-service banks that only accept deposits and payments. We include the latter type of banks to capture the effect of banking hinterlands, or commuting zones without any main bank offices, on the distribution of PPP loans. The county data is again aggregated up to the CZ level. The NCUA Quarterly Call Report Data for the second quarter of 2020 are used to get a list of all credit unions by location. Credit Unions are only listed by address without their county of residence, so we follow a similar zip code to county procedure as with the PPP loan data before we aggregate these to the commuting zone. The number of credit unions are combined with the number of banks to create a total measure of bank concentration for each CZ.

Buyers of loans are most likely to choose banks that are either close to home or workplace. In terms of the status of the local economy, we focus on the employment/population ratio as an indicator of job opportunity available to the region's population following the significant downturn in March/April 2020, as well as the proportion of citizens with a higher-education degree and per capita GDP. Amior and Manning underscore the employment/population ra-

Table 1: Summary Statistics

	mean	sd	min	max	count
PPP Loans per Small Business	1.83	1.05	0.34	10.19	706
PPP Loan Amount per Small Business	84842.48	22485.98	12751.05	216613.64	706
Rounds 1+2 Loans per Small Business	0.68	0.20	0.18	1.91	706
Round 3 Loans per Small Business	1.15	0.89	0.12	8.76	706
Rounds 1+2 Loan Amount per Small Business	52574.19	13644.58	8425.66	134863.17	706
Round 3 Loan Amount per Small Business	32268.30	13926.76	4325.39	148088.13	706
Banks + C.U.s per 10k people	4.49	2.91	0.00	37.83	706
Bank Headquarters per 10k people	0.64	0.97	0.00	9.65	706
COVID-19 Cases per 10k people	2.81	5.76	0.00	88.29	706
$\frac{Employment}{Population}$	0.45	0.06	0.24	0.83	706
$\frac{Median HH.Inc.}{Mean HH.Inc.}$	0.75	0.04	0.60	0.90	706
GDP per Capita (Thousands)	54.04	25.50	22.77	392.17	706
Population Density (Thousands/sq.mi)	0.01	0.03	0.00	0.75	704
Share of Pop. with at least a B.A.	0.24	0.08	0.07	0.56	706
Non-White Population Share	0.18	0.16	0.01	0.89	706
Small Businesses per 10k people	252.72	88.48	48.99	1097.14	706
Share of Small Businesses <10 Employees	0.75	0.05	0.62	1.00	706
Share of Small Businesses <50 Employees	0.96	0.02	0.92	1.00	706

tio as being a particular appropriate measure of economic opportunity (Amior and Manning, 2018), which we leverage in this work.

Table 1 presents summary statistics for each of the variables in our sample. The final sample consists of 706 commuting zones and over 11.7 million individual loans. The third wave of PPP loans allowed for small businesses to reapply for a second and in many cases a third PPP loan. As a result, we observe that in the final wave, there are a large number of loans originated, but at a lower average loan amount than in the initial waves.

To account for population differences across CZs, we normalize the number of banks, credit unions, and bank headquarters by the number of small business in a CZ. We also normalize COVID-19 cases and the number of small businesses by CZ population per ten thousand in regional population, in the spirit of Amior and Manning (2018).

Figure 1 maps the geographic dispersion of PPP loans per SBA small business. Interestingly, the highest concentrations of PPP loans per small business occurred throughout the Great Plains, Midwestern and Southern states.

Throughout this work, we compare the density of PPP loans to the density of bank and credit union locations per 10k population. Figure 2 maps the concentration of bank and credit union branches across United States Commuting Zones. There appears to be a high degree of spatial correlation between the areas with a high density of lenders and areas with a high density of PPP loans. To account for potential spatial clustering, our models to follow include both White (1980) robust standard errors (listed in parenthesis), and Conley (1999) spatially robust errors [listed in brackets].

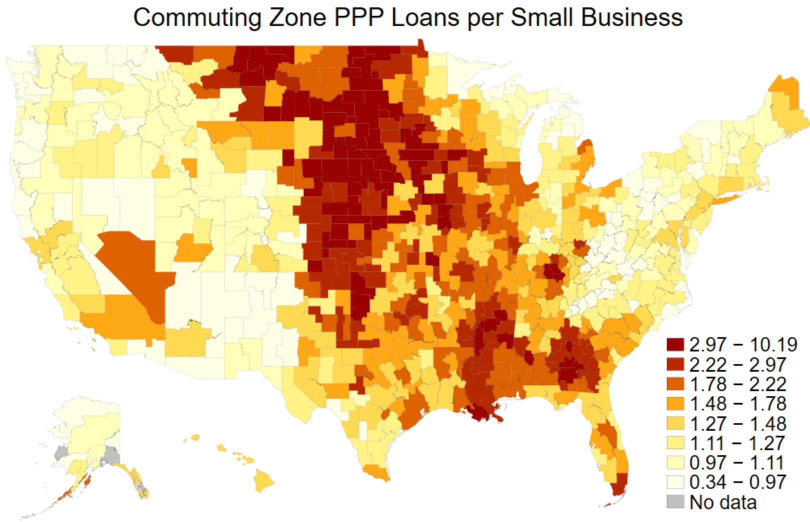


Figure 1: Density of PPP Loans per Small Business by County

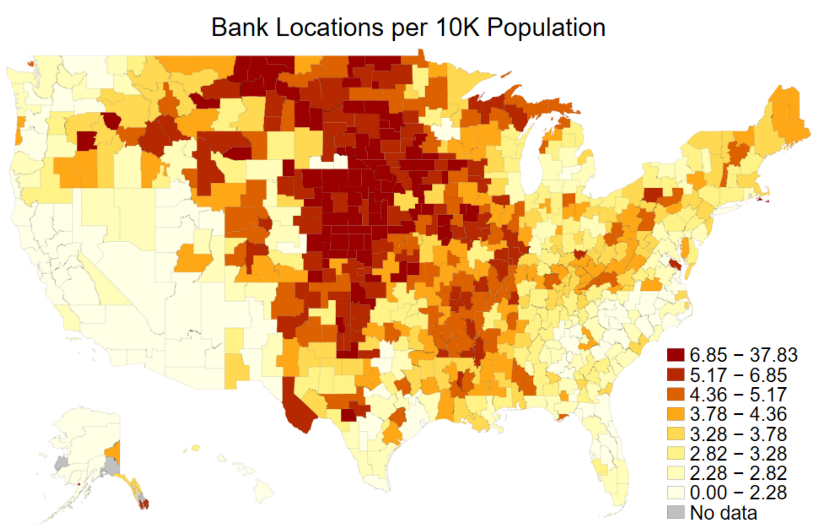


Figure 2: Density of Bank Locations per 10K Population by County

3. BANK DENSITY AND PPP LOAN ALLOCATION

Our approach follows clues left by the handful of studies on PPP loan distribution. Amiram and Rabetti (2020) and Li and Strahan (2021) find those establishments with existing banking relationships tended to get loans first and in the largest amounts. We indirectly test both propositions in the present work, in particular through the resource flows channeled towards the smallest businesses which are less likely to have established banking relationships. Granja et al. (2022) further find that those relationships tended to outweigh stated goals of the program, namely targeting those areas and businesses in greatest need of loans due to the pandemic.

Barrios et al. (2020) find that establishment payrolls closely predict PPP loan receipts, indicating there may be a positive relationship between business size and loan disbursement. We test this proposition empirically as well, but do not find significant effects among small businesses of less than 10 or less than 50 employees. Finally, Fairlie and Fossen (2022) find that early loans went mainly to non-minority applicants, while the later waves flowed more to these marginalized populations. We follow their lead in testing the significance on non-white shares of commuting zone populations on loan disbursement. Including the non-white population share likely does not control for banking discrimination, but instead picks up more broadly on forms of discrimination may both limit banking opportunities within a Commuting Zones and cause economically marginalized groups to migrate elsewhere. To minimize concerns about collider bias, we present results in Tables A1-A3 without covariates. The inclusion of the non-white population share does not on its own alter the interpretation of the main relationship of interest, between bank density and loan dispersion.

The implications of systematic informational asymmetries based on geography can fundamentally shift innovation and resources away from lagging regions, further entrenching their economic struggles (Weiler, 2000). These geographic information asymmetries (GIA) are most likely to be felt in business-to-business transactions built on the supplier's understanding of those demanding services. Small business lending may be particularly vulnerable to GIA discrimination, given its reliance on credit scoring developed at a bank's headquarters – which may not be congruent with the realities of a rural economy – as well the past viability of similar projects. The latter will be a particularly high hurdle for innovative projects that have no track record in the focal economy. Rural areas tend to have thin informational markets due to lower establishment dynamism and thus fewer datapoints from which to extract the viability of loans (Bunten et al., 2015).

Statistically, the perception of otherwise identical probability distribution of outcomes in two regions will have lower variance in the market with thicker information through greater past business experience. In contrast, the thin market featuring fewer datapoints will lead to higher perceived variance of outcomes, heightening uncertainty and thus risk for bankers (Weiler et al., 2006). These risks may deter bankers from making loans to those companies without existing intensive relationships, leading to disproportionate flows towards advantaged regions and businesses. These informational asymmetries may thus be a driving force for systematic discrimination of PPP loans towards those thick-market regions that have denser labor markets as measured by the employment/population ratio, established banking networks, and larger establishments. Our empirical work tests these propositions.

This paper investigates whether the distribution of banks and banking hinterlands partially determined the distribution of PPP loans. Since the PPP loans were distributed through banks and a limited amount of initial funds, we hypothesize that regions with a greater concentration of banks as well as bank headquarters received more PPP loans, and that banking deserts and banking hinterlands were systematically disadvantaged in PPP allocations. We take the geographic distribution of banks as being given a priori, and thus exogenous to the analysis. A higher concentration of banks provides more opportunities for small businesses to find a bank that had not already exhausted their allotment of PPP funding.

We are specifically also interested in whether loans went to the small businesses that were avowedly priorities for the program. To empirically test these hypotheses, we estimate the following equation:

$$Y_i = \beta_0 + \beta_1 \text{Bank Concentration}_i + \beta_2 \text{Bank HQ}_i + \beta_4 \text{COVID-19 Cases}_i + \Gamma X_i + \epsilon \qquad (1)$$

Where Y_i are the outcome variables of interest, in this case PPP loans per small business and PPP loan amount per small business at the Commuting Zone level, X is a matrix of Commuting Zone covariates, and Γ is a vector of coefficients.

Bank Concentration is the number of banks and credit unions per 10,000 people in CZ i, Bank HQ is the number bank main offices per 10,000 people in CZi, COVID case count at initiation of the CARES act is the commuting zone number of COVID-19 cases per 10,000 people from New York Times counts. The matrix X contains the share of non-White population in CZ i, the CZ-level share of businesses that have fewer than 50 or fewer than 10 employees out of all small businesses, the commuting zone-level employment-to-population ratio for April 2020, a commuting zone-level measure of inequality measuring the ratio of household median income to household mean income, the per capita GDP of CZ, and population density measured as total population divided by land area in square miles. i, and the share of the CZ population that has at least a bachelor's degree in CZ i. ϵ_i is an idiosyncratic error term.

Variance Inflation Factor (VIF) analyses indicate that there was no substantive multicollinearity among the explanatory variables. We fully acknowledge that the cross-sectional dataset can offer only a limited view of PPP impacts, given that the data show only transacted loans. The lack of application data would tend to upwardly bias the findings by overstating the effect of local banks, making our results an upper-bound of the PPP effect.

Coefficients β_1 and β_2 are our main coefficients of interest. Consistent with our banking desert and banking hinterland hypotheses, we expect both coefficients to be positive for all outcomes of interest, as more loans flow to those areas with more banks and more bank headquarters rather towards banking deserts and hinterlands.

We are also interested in a question of intensity. In the areas with the most PPP loans per small business, is the relationship between of bank density and loan density different than in areas which recieved fewer loans per business? To answer this question, we first look at the impact of squared bank location density.

3.1. Loans and Loan Amounts per SBA Small Business

Table 2 presents results from an OLS model with both Huber-White robust and Conley (1999) spatially robust standard errors. Columns 1 and 2 report models for the number of PPP loans per small business with and without Commuting Zone controls, while Columns 3 and 4 report specifications with PPP loan amount per small business as the independent variable. We find a positive and significant relationship between both independent variables of interest: bank locations and bank headquarters, and both outcomes of interest: loans and loan amount per small business. These results are robust to inverse distance spatial weighting with a distance cutoff of two degrees latitude, or about 140 miles.

We find that an increase of one bank location (22% increase from the mean) per 10,000 people is associated with an increase of about .33 PPP loans per small business (18% increase from the mean), and an increase in total loan amount of $4775 per small business (6% increase from the mean) in the Commuting Zone. We are also interested in whether communities at need as defined by exposure to COVID-19 received more loans. We find that COVID-19 case load was not associated with the number of loans in the Commuting Zone, but was associated with a larger loan amount per small business.

In columns 2 and 4 of Table 2 we also consider the intensity of banking services in a commuting zone. We add a squared banking density term to Equation 1 to further investigate how the intensity of bank concentration relates to the distribution of PPP loans. This allows us to measure whether there are increasing, constant, or diminishing returns to increased banking intensity. A positive (negative) coefficient on the squared term would indicate increasing (decreasing) returns to greater concentrations of banks while a zero or null effect may indicate constant returns. In the presence of decreasing returns, we can also calculate the level at which an increased concentration of banking services no longer associated with an increase in PPP loans. We report the results of this inclusion in Table 2 and Table 3.

Table 2 shows that there is an association between areas with a greater concentration of banks and credit unions and areas that received more PPP loans. We do find, by including the square of the banking variable, that bank concentration exhibits diminishing returns. Once the concentration of banks and credit unions is greater than 24.93 banks per 10,000 people, which is around the 70th percentile, the number of PPP loans is negatively associated with additional banks in the commuting zone. Even before that level, each additional increase in the concentration of banks associated with smaller increases in the number PPP loans, however, diminishing returns to additional banks do not seem to set in until higher percentiles of density. This suggests that in low bank concentration areas, an additional bank is helpful for small businesses applying for PPP loans, but are less helpful in areas with an abundant number of banks.

The same pattern holds when examining the number of loans per small business across the three waves of PPP funding in Table 3. Increases in banking concentration exhibit diminishing returns for each of the three rounds of PPP funding, though the level at which an additional bank becomes detrimental in obtaining a PPP loan are are different for each round. The benefits of an additional bank reach their peak at 18.92 banks per 10,000 people in round 1, 28.5 banks per 10,000 people in round 2, and 34.61 banks per 10,000 people in the final round of funding. The changes in the amount of funding for each round may

Table 2: PPP Loans and PPP Loan Amount per Small Business

	(1) PPP Loans	(2) PPP Loans	(3) PPP Amount ($K)	(4) PPP Amount ($K)
Banks + C.U.s per 10k people	0.1447	0.3299	1.0106	4.7754
	(0.0269)***	(0.0323)***	(0.4586)**	(0.8487)***
	[0.0290]***	[0.0358]***	[0.4390]**	[0.8155]***
Bank Headquarters per 10k people	0.4415	0.2693	6.1301	5.7286
	(0.0908)***	(0.0697)***	(1.9084)***	(1.8772)***
	[0.0975]***	[0.0760]***	[1.8080]***	[1.6960]***
(Banks + C.U.s per 10k)^2		-0.0054		-0.1047
		(0.0009)***		(0.0189)***
		[0.0009]***		[0.0196]***
COVID-19 Cases per 10k people		0.0014		0.2905
		(0.0046)		(0.1585)*
		[0.0054]		[0.1754]*
Employment/Pop		4.6702		128.8527
		(0.7634)***		(16.6494)***
		[0.8241]***		[18.4694]***
Inequality		-0.6198		25.3039
		(0.8274)		(20.6096)
		[0.8358]		[21.8599]
GDP per Capita in Thousands		-0.0031		0.0925
		(0.0011)***		(0.0713)
		[0.0012]***		[0.0725]
Non-White Population Share		2.4094		48.5135
		(0.2851)***		(6.0884)***
		[0.3762]***		[7.0908]***
Small Businesses per 10k people		-0.0040		-0.0210
		(0.0007)***		(0.0158)
		[0.0007]***		[0.0175]
Share of Small Businesses <10 Employees		2.4628		-120.5275
		(2.3446)		(48.4854)**
		[2.4167]		[46.1229]***
Share of Small Businesses <50 Employees		4.2518		-113.2127
		(7.0712)		(142.1779)
		[7.6797]		[148.8537]
Population Density		-0.1073		16.0332
		(0.4333)		(31.9671)
		[0.5005]		[31.0523]
PPP Loans			0.0003	0.0002
			(0.0001)***	(0.0001)**
			[0.0001]***	[0.0001]***
Constant	0.8951	-6.5208	73.9047	173.5806
	(0.0818)***	(5.3929)	(1.7573)***	(108.4098)
	[0.1200]***	[6.0306]	[2.0878]***	[119.6468]
Observations	704	704	704	704
R^2	0.525	0.693	0.190	0.495
F	107.34	66.46	20.63	51.01

Note: Huber-White standard errors in parentheses. Conley (1999) Standard errors are in brackets. A cutoff distance of 2 degrees (222.28 km) was used for both latitude and longitude. $*\ p < 0.10$, $**\ p < 0.05$, *and* $***\ p < 0.01$.

be responsible for the changing inflection point at which there is no longer a benefit to an additional bank in the disbursement of PPP loans. With more funding available in the second and third rounds, more banks would ease congestion and make it easier for more small businesses to obtain help through the program. Despite only three commuting zones being affected by any of these concentration thresholds, these result suggest that areas with a higher concentration of banks received more PPP loans but that each additional bank had less of an impact in increasing the total number of loans allocated to that place.

As a robustness check, we normalize our bank + credit union and headquarters density measures per SBA small business as Appendix Table A4. Rescaling bank density per small business may better capture local competition in the commuting zone's supply of financial capital. The number of banks + credit unions per small business (0.017) is very small compared to per 10k population (4.49). As a result, the interpretation of a change in one banking location per small business is less clean. However, we do confirm that the positive and signficant relationship between bank, headquarters locations and loan density holds.

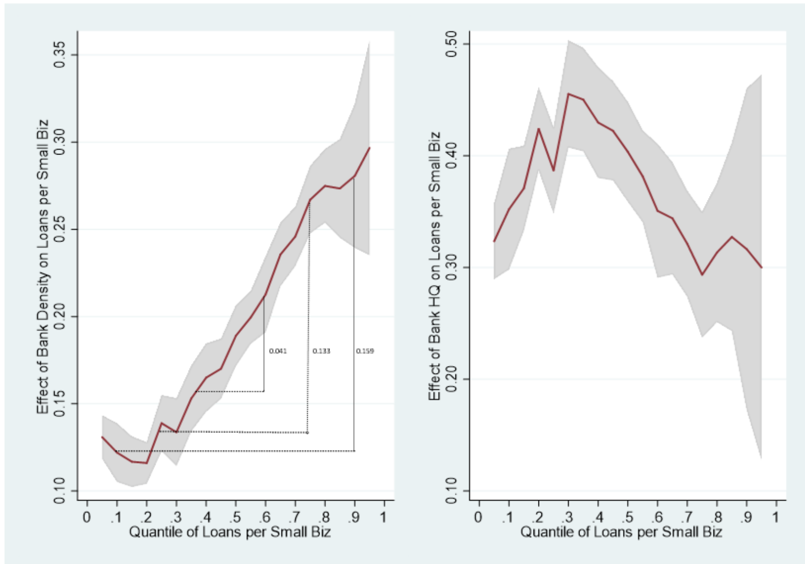
3.2. Timing Across PPP Loan Waves

Because we may be interested in the progression of the relationship between bank locations, headquarters and PPP loan dispersion, Tables 3 and 4 present the results on PPP loans and PPP loan amount per capita, broken down into each of the three waves of PPP loans defined in the preceding section. For ease of reading, we present the model with controls in all three periods in the main text. We also include in the Appendix the same models without controls as Tables A1 and A2. With regard to PPP loans per small business, we find that the positive and significant relationship with bank and credit union locations per 10,000 people holds across all three loan periods, but is much stronger in the final wave, post- August 8, 2020. The same holds for bank headquarters locations with a positive and significant coefficient across all three periods, strongest in the last. In the PPP loan amounts model, we find that a positive and significant relationship with bank density holds across all three lending periods. However, a positive and significant relationship between bank headquarters and loan amounts holds only in the final wave of lending.

These results are closely aligned with a general trend of PPP lending across waves, which was that initial periods saw relatively fewer loans issued of larger amounts, while later periods included larger volumes of lower value loans. These trends in part reflect changes in eligibility requirements for the loans. For example, nonemployer businesses which make up about 80% of all businesses in the United States, were largely ineligible until the second round of lending. As the pandemic continued from Summer 2020 into Spring 2021, additional emphasis was placed on distributing relief funds to at-need areas as quickly as possible, which helps explain the high loan densities in the final rounds of lending. Businesses were also eligible to re-apply for a second and in some cases third round of loans in the later period, which could also inflate loan density per small business.

To further isolate the potential role of bank density in explaining PPP loan density, we pool the three waves together with Commuting Zone fixed effects as a repeated cross section in Appendix Table A5. Rules around who could service the loans and which businesses were eligible to apply and reapply shifted between the first and third waves, as did the

Figure 3: Graph of Quantile Regression Coefficients



pool of workers who were deemed as 'essential'. To test differences across lending waves we control for potential unobserved time invariant factors across Commuting Zones, or spurious correlation with other local conditions, which could have been incorrectly attributed to bank density in Tables 2-4. We find that the coefficient on both bank and headquarters density in the loan density model is significantly higher in the final round of lending, confirming the findings in Table 3. Likewise, in comparison to Table 4, we find that although loan amounts were highest in the first round of lending, the impact of bank and headquarters density is strongest in the final wave of lending.

3.3. Regression on Quantiles of Loan Dispersion

Returning again to the question of the intensity of the relationship between banking density and loan density, we implement a quantile regression approach on quantiles of loans per small business and loan amount per small business, estimated by minimizing an asymmetrically weighted sum of absolute errors (Koenker and Hallock, 2001).

Figure 3 maps the coefficient in the regression equation (1) across all possible quantiles of the outcome variables: loans per small business and loan amount per small business. In Commuting Zones which received the highest density of loans per small business, the coefficient in the loan density model is the largest. That is, as the density of PPP loans per small business increases, the relationship between loans per small business and bank density, as measured by a quantile regression framework, becomes more statistically differentiable from zero.

The quantile regression methodology is useful for understanding relationships between variables outside of their conditional means. To test how the relationship between banking locations and PPP loans varies across quantiles of PPP loans, in Table 5 we present the results of interquantile regressions at the (.6 vs .4), (.75 vs .25), and (.9 vs .1) quantiles.

Table 3: PPP Loans per Small Business by Round

	(1) Round 1 Loans	(2) Round 2 Loans	(3) Round 3 Loans
Banks + C.U.s per 10k people	0.0454	0.0285	0.2561
	(0.0047)***	(0.0052)***	(0.0307)***
	[0.0042]***	[0.0060]***	[0.0342]***
Bank Headquarters per 10k people	0.0139	0.0194	0.2360
	(0.0094)	(0.0084)**	(0.0683)***
	[0.0079]*	[0.0074]***	[0.0765]***
(Banks + C.U.s per 10k)^2	-0.0012	-0.0005	-0.0037
	(0.0001)***	(0.0002)**	(0.0009)***
	[0.0001]***	[0.0002]**	[0.0009]***
COVID-19 Cases per 10k people	-0.0010	0.0017	0.0007
	(0.0005)**	(0.0007)**	(0.0041)
	[0.0005]**	[0.0008]**	[0.0048]
Employment/Pop	0.4540	0.6294	3.5868
	(0.1027)***	(0.0824)***	(0.7383)***
	[0.1069]***	[0.0916]***	[0.7897]***
Inequality	0.1748	-0.1382	-0.6564
	(0.1106)	(0.1086)	(0.7686)
	[0.1372]	[0.1202]	[0.7548]
GDP per Capita in Thousands	-0.0005	0.0001	-0.0027
	(0.0002)***	(0.0003)	(0.0010)***
	[0.0002]***	[0.0003]	[0.0011]**
Non-White Population Share	0.0623	0.2307	2.1165
	(0.0271)**	(0.0319)***	(0.2622)***
	[0.0329]*	[0.0354]***	[0.3501]***
Small Businesses per 10k people	-0.0001	-0.0003	-0.0036
	(0.0001)	(0.0001)***	(0.0007)***
	[0.0001]	[0.0001]***	[0.0007]***
Share of Small Businesses <10 Employees	-0.4115	0.5900	2.2843
	(0.1660)**	(0.2466)**	(2.2017)
	[0.1729]**	[0.2510]**	[2.2530]
Share of Small Businesses <50 Employees	0.6788	-0.3737	3.9466
	(0.4702)	(0.7267)	(6.5131)
	[0.5015]	[0.7571]	[7.1006]
Population Density	-0.3134	0.4393	-0.2332
	(0.1771)*	(0.2358)*	(0.4008)
	[0.1717]*	[0.2305]*	[0.4504]
Constant	-0.5228	0.0096	-6.0076
	(0.4152)	(0.5551)	(4.9337)
	[0.4582]	[0.5928]	[5.5567]
Observations	704	704	704
R^2	0.565	0.429	0.661
F	54.75	27.97	52.12

Note: Huber-White standard errors in parentheses. Conley (1999) Standard errors are in brackets. A cutoff distance of 2 degrees (222.28 km) was used for both latitude and longitude. $*\, p < 0.10$, $**\ p < 0.05$, *and* $***\ p < 0.01$.

Table 4: PPP Loan Amount per Small Business by Round

	(1) Round 1 Amount ($K)	(2) Round 2 Amount ($K)	(3) Round 3 Amount ($K)
Banks + C.U.s per 10k people	2.7781	-1.4122	3.2945
	(0.4932)***	(0.2903)***	(0.5709)***
	[0.4820]***	[0.3218]***	[0.6025]***
Bank Headquarters per 10k people	0.6309	0.6270	4.4323
	(1.1302)	(0.4635)	(1.2457)***
	[1.1179]	[0.5223]	[1.2384]***
(Banks + C.U.s per 10k)^2	-0.0797	0.0349	-0.0571
	(0.0121)***	(0.0132)***	(0.0141)***
	[0.0118]***	[0.0137]**	[0.0150]***
COVID-19 Cases per 10k people	0.0199	0.1287	0.1358
	(0.0531)	(0.0424)***	(0.0915)
	[0.0596]	[0.0471]***	[0.1022]
Employment/Pop	53.5796	15.7834	59.5934
	(10.3787)***	(5.3623)***	(13.2768)***
	[10.5724]***	[5.4558]***	[14.3362]***
Inequality	26.1679	-5.5050	1.6039
	(12.2139)**	(6.1777)	(14.8493)
	[13.5412]**	[6.2411]	[15.0256]
GDP per Capita in Thousands	0.0200	0.0531	0.0169
	(0.0231)	(0.0231)**	(0.0472)
	[02040]	[0.0230]**	[0.04789]
Non-White Population Share	6.4771	3.9525	37.9301
	(3.0467)**	(1.8084)**	(4.3394)***
	[3.4482]*	[1.8888]**	[5.4927]***
Small Businesses per 10k people	0.0092	-0.0080	-0.0227
	(0.0097)	(0.0052)	(0.0115)**
	[0.0098]	[0.0053]	[0.0123]*
Share of Small Businesses <10 Employees	-104.5639	7.9850	-23.1913
	(20.9340)***	(13.2155)	(40.2835)
	[20.5401]***	[12.5844]	[39.7444]
Share of Small Businesses <50 Employees	-191.1702	29.2026	43.8916
	(61.6154)***	(41.3183)	(109.4726)
	[65.2340]***	[40.5638]	[115.8543]
PPP Loans	0.0000	0.0001	0.0001**
	(0.0000)	(0.0000)***	(0.0000)
	[0.0000]	[0.0000]***	[0.0000]**
Population Density	-1.3626	15.2125	3.3293
	(6.5358)	(18.7966)	(11.2152)
	[6.6232]	[17.8955]	[11.3369]
Constant	240.0579	-19.5853	-39.7466
	(48.7813)***	(31.7068)	(82.0903)
	[53.3138]***	[31.5116]	[90.2629]
Observations	704	704	704
R^2	0.455	0.397	0.513
F	41.46	20.10	47.58

Note: Huber-White standard errors in parentheses. Conley (1999) Standard errors are in brackets. A cutoff distance of 2 degrees (222.28 km) was used for both latitude and longitude. $*\,p < 0.10$, $**\,p < 0.05$, *and* $***\,p < 0.01$.

These statistically significant differences are also illustrated in the left panel of Figure 3, but do not hold in the bank headquarters regression.

When comparing the 60th vs 40th percentiles of PPP loans per small business, we note a slightly stronger effect at the 60th percentile, significant with 10% confidence. As we widen the gap in commuting zone loans per small business to look at the 75th vs 25th and 90th vs 10th percentiles, we observe that the difference in the relationship between bank density and loans grows. In commuting zones at the 90th percentile of loans per small business, each additional bank or credit union location per 10K population would correspond to about .16 more loans per small business than at the 10th percentile. This suggests that the relationship between bank density and loan density may be more meaningful in commuting zones with high loan densities. We do not observe a similar pattern in the relationship between banking headquarters and loan density.

Further research is warranted to determine why bank density was closely related to loans per small business in the commuting zones with the most loans. One possible explanation lies in the origination fee structure for the loans. At the beginning of the program, lenders earned origination fees on loans in the amount of 5% of the loan up to $350K, 3% of loans between $350K and $2M and 1% of loans larger than $2M. In December 2020, the servicing fee structure was revised so that lenders earned the minimum of 50% of the loan or $2500 for loans under $50K, and 5% of loans between $50-350K, with the remaining fee structure unchanged. Competition for servicing fees may have been a powerful incentive to rapidly originate PPP loans, especially among small banks. Regulatory data shows differences between large and small banks' response to the PPP program with large bank loan originations are smaller than predicted based on operational characteristics and historical lending patterns (Kupiec, 2021). The incentive of a reasonably high fee for even smaller loans is a potential explanation for the spike in loan density per small business in the final lending period. Additional forthcoming research by the authors explores incentives created by the origination fees, and by discontinuities in the fee structure.

4. CONCLUSION

The Paycheck Protection Program was an important federal government response to the COVID-19 outbreak of 2020. In the span of just over a year, almost $800 billion in funds were allocated as part of an ongoing effort to thwart widespread unemployment. Previous literature studies the dispersion of PPP loans in the context of bank size and health, and the impact on communities and jobs. However, there has been to date limited academic study of the geospatial dispersion of PPP loans.

This paper makes three main contributions to the literature. First, we revisit previous results from Deming and Weiler (2023) which find a significant positive relationship between the density of banking locations and PPP loans. These results are an improvement on past work because we now use more accurately geocoded loans data which removes erroneous zero or near zero values in a handful of rural Commuting Zones. We confirm that there is a positive and statistically significant relationship between bank location density and PPP loans per small business. An additional bank location per 10K population is associated with an increase of .33 loans per small business, or about 18% from the mean.

Table 5: Interquantile Regressions of PPP Loan per Small Business

	(1) (.6 vs .4) PPP Loans	(2) (.75 vs .25) PPP Loans	(3) (.9 vs .1) PPP Loans
Banks + C.U.s per 10k people	0.041*	0.133***	0.159***
	(0.023)	(0.034)	(0.033)
Bank Headquarters per 10k people	-0.079	-0.102	0.061
	(0.067)	(0.076)	(0.093)
COVID-19 Cases per 10k people	0.005	0.006	0.003
	(0.005)	(0.005)	(0.006)
Employment/Pop	0.770	1.688*	3.516**
	(0.494)	(0.982)	(1.432)
Inequality	0.109	-0.848	-1.491
	(0.576)	(0.716)	(1.074)
GDP per Capita in Thousands	0.000	-0.000	-0.000
	(0.001)	(0.002)	(0.004)
Non-White Population Share	0.542**	1.636***	2.511***
	(0.264)	(0.457)	(0.463)
Small Businesses per 10k people	-0.001	-0.001**	-0.002**
	(0.000)	(0.001)	(0.001)
Share of Small Businesses <10 Employees	0.435	0.375	-0.102
	(1.075)	(2.082)	(2.830)
Share of Small Businesses <50 Employees	2.835	8.690	22.311**
	(3.476)	(6.282)	(9.449)
Population Density	-0.419	0.188	2.623
	(1.109)	(2.163)	(2.159)
Constant	-3.169	-8.327*	-20.577***
	(2.870)	(5.046)	(7.347)
Observations	704	704	704

Huber-White standard errors in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Second, we expand upon previous literature by considering loans issued across three waves of the PPP program. Loans were decomposed into periods reflecting guidance issued by the SBA. A first lending period lasted from the initiation of the program for about two weeks until funds ran out. A week later, a second lending period began following additional congressional approval. When that period expired with remaining funds still unclaimed, a third lending period began which expanded the pool of potential lenders. We find that there is a significant and positive relationship between bank and loan density across all loan periods, but strongest in the last. In a pooled cross section, we find that the response of loan volume to bank density was largest in the final wave of lending.

Finally, this paper considers differences in the relationship between bank density and loans per small business across all values of loan density. We show that the relationship between bank and loan density is the most intense in commuting zones which received the largest number of loans per small business. In light of literature suggesting that smaller banks originated larger than expected shares of the loans, we suggest that further research is warranted to determine whether the loan origination fee structure might have created competition to originate larger volumes of loans among smaller banks.

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A. APPENDIX A

Table A1: PPP Loans per Small Business by Round (No Controls)

	(1) R1 Loans	(2) R2 Loans	(3) Round 3 Loans
Banks + C.U.s per 10k people	0.019***	0.011**	0.114***
	(0.006)	(0.005)	(0.020)
Bank Headquarters per 10k people	0.033**	0.037***	0.373***
	(0.013)	(0.010)	(0.084)
Constant	0.193***	0.310***	0.398***
	(0.018)	(0.015)	(0.060)
Observations	706	706	706
R^2	0.420	0.238	0.482
F	71.155	62.021	102.735

Notes: Results of this Table compare to those in Table 3. We verify that the results presented are not driven by the inclusion of Commuting Zone level covariates. Huber-White standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

Table A2: PPP Loan Amount per Small Business by Round (No Controls)

	(1) R1 Amount ($K)	(2) R2 Amount ($K)	(3) Round 3 Amount ($K)
Banks + C.U.s per 10k people	167.802	-755.354***	1131.911***
	(290.716)	(171.047)	(300.879)
Bank Headquarters per 10k people	30.080	178.494	5305.306***
	(1285.556)	(559.421)	(1348.830)
Constant	36501.890***	18658.598***	23812.483***
	(929.633)	(658.227)	(916.448)
Observations	706	706	706
R^2	0.002	0.089	0.300
F	0.487	17.509	67.554

Notes: Results of this Table compare to those in Table 4. We verify that the results presented are not driven by the inclusion of Commuting Zone level covariates. Huber-White standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

Table A3: Interquantile Regression of PPP Loans per Small Business (No Controls)

PPP Loans	(1) (.6 vs .4) PPP Loans	(2) (.75 vs .25) PPP Loans	(3) (.9 vs.1)
Banks + C.U.s per 10k people	0.055**	0.116***	0.218***
	(0.027)	(0.037)	(0.040)
Bank Headquarters per 10k people	-0.058	-0.021	0.028
	(0.064)	(0.095)	(0.138)
Constant	0.020	0.174	0.465***
	(0.076)	(0.114)	(0.137)
Observations	706	706	706

Notes: Results of this Table compare to those in Table 5. We verify that the results presented are not driven by the inclusion of Commuting Zone level covariates. Huber-White standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

Table A4: Bank Density Scaled per Small Business (compare to Table 2)

	(1) PPP Loans per Small Business	(2) PPP Loans per Small Business	(3) PPP Loan Amount per Small Business	(4) PPP Loan Amount per Small Business
Banks + C.U.s per Small Business	63.696***	66.027***	7383.165	6.74e+05***
	(7.556)	(6.374)	(1.83e+05)	(1.88e+05)
Bank Headquarters per Small Business	102.713***	71.589***	1.68e+06***	1.70e+06***
	(20.014)	(16.070)	(5.45e+05)	(4.76e+05)
COVID-19 Cases per 10k people		0.001		294.606*
		(0.005)		(168.949)
Employment/Pop		6.830***		1.57e+05***
		(0.667)		(18765.644)
Inequality		-0.375		28092.444
		(0.694)		(20807.373)
GDP per Capita in Thousands		-0.004***		81.949
		(0.001)		(67.624)
Share of Pop. with at least a B.A.		-2.325***		-3.16e+04**
		(0.421)		(14217.670)
Non-White Population Share		2.436***		45931.434***
		(0.266)		(6113.676)
Small Businesses per 10k people		0.001		38.543**
		(0.000)		(16.611)
Share of Small Businesses <10 Employees		0.973		-1.43e+05***
		(1.745)		(44199.846)
Share of Small Businesses <50 Employees		7.102		-4.15e+04
		(5.406)		(1.28e+05)
Population Density		0.996		20884.519
		(0.713)		(36020.596)
Total CZ PPP Loans				0.077***
				(0.026)
Constant	0.506***	-9.706**	80621.683***	1.06e+05
	(0.086)	(4.277)	(2349.256)	(98590.996)
Observations	706	704	706	704
R^2	0.553	0.703	0.066	0.478
F	182.005	73.388	11.584	41.102

Notes: A higher relative density of banks to small businesses may be a better representation of local competition than banks scaled per population. In this table we verify that the rescaling doesn't change the direction of the relationship of interest. Huber-White standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

Table A5: PPP Loans and PPP Loan Amount per Small Business

	(1) PPP Loans per Small Business	(2) PPP Loan Amount per Small Business
R1 × Banks + C.U.s per 10k people	-0.132***	-0.914**
	(0.021)	(0.392)
R2 × Banks + C.U.s per 10k people	-0.131***	-2.124***
	(0.021)	(0.491)
R1 × Bank Headquarters per 10k people	-0.242***	-3.260**
	(0.062)	(1.587)
R2 × Bank Headquarters per 10k people	-0.241***	-4.754***
	(0.062)	(1.218)
R1 × COVID-19 Cases per 10k people	-0.005	-0.167***
	(0.004)	(0.059)
R2 × COVID-19 Cases per 10k people	-0.002	-0.040
	(0.003)	(0.082)
R1 × Employment/Pop	-4.066***	-16.169
	(0.723)	(16.966)
R2 × Inequality	-4.124***	-65.643***
	(0.725)	(13.202)
R1 × GDP per Capita in Thousands	0.003***	0.018
	(0.001)	(0.047)
R2 × GDP per Capita in Thousands	0.004***	0.047
	(0.001)	(0.032)
R1 × Share of Pop. with at least a B.A.	2.169***	27.290***
	(0.375)	(9.355)
R2 × Share of Pop. with at least a B.A.	2.381***	40.236***
	(0.375)	(8.985)
R1 × Non-White Population Share	-2.065***	-34.506***
	(0.268)	(5.243)
R2 × Non-White Population Share	-1.904***	-31.894***
	(0.260)	(4.442)
R1 × Small Businesses per 10k people	0.003***	0.021
	(0.001)	(0.015)
R2 × Small Businesses per 10k people	0.002***	-0.004
	(0.001)	(0.010)
R1 × Share of Small Businesses <10 Employees	-2.705	-79.498
	(2.222)	(50.778)
R2 × Share of Small Businesses <10 Employees	-1.919	27.357
	(2.114)	(34.055)
R1 × Share of Small Businesses <50 Employees	-3.115	-213.697
	(6.700)	(140.501)
R2 × Share of Small Businesses <50 Employees	-3.745	-23.949
	(6.325)	(93.822)

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	(1) PPP Loans per Small Business	(2) PPP Loan Amount per Small Business
R1 × Total CZ PPP Loans	-0.001*	-0.001***
	(0.001)	(0.001)
R2 × Total CZ PPP Loans	-0.001	0.0001
	(0.001)	(0.001)
R1 × Population Density	0.399	-5.435
	(0.700)	(14.063)
R2 × Population Density	0.537	17.565
	(0.492)	(11.155)
R1	5.836	278.278***
	(5.043)	(101.770)
R2	5.911	22.609
	(4.772)	(70.294)
Constant	1.146***	32.256***
	(0.012)	(0.227)
Observations	2112	2112
R^2	0.866	0.811
F	116.491	147.220
Fixed Effects	CZ	CZ

Notes: To conduct this analysis, Commuting Zones were pooled into a repeat cross section with three observations per CZ. Cross-sectional covariates are dropped as multicollinear. We demonstrate that the relationship between bank density and loan density, loan amount is strongest in the final round of lending. Huber-White standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$