Benefits of PPP Lending Through Community Banks During the COVID-19 Recession

Paper for the CSBS Banking Analytics Competition

University of California at Irvine

Abhishek Karimpuzha Devarajan
Qi Wang
Qingqing Yu
Wanjing Xu
Yixuan Cai

Academic Adviser: Professor Gary Richardson

Abstract

During the COVID-19 pandemic, the Paycheck Protection Program (PPP) was designed to keep small businesses running and reduce unemployment. Preliminary research done by CSBS suggests that community banks played a large role in distributing PPP loans to small businesses. In this paper, we examine the effect of PPP lending by community banks on the county-level unemployment in 2020 and 2021.Our regression model reveals that community banks lending decreased unemployment more than comparable lending of non-community bank lending. Possible explanations for our finding include the speed that the community issues the loans, the high forgiveness rate of loans extended by community banks, and the industrial composition of PPP loans by community banks.

1. Introduction

The 2022 Conference of State Bank Supervisors' (CSBS) annual Data Analytics Competition asks us to examine the role that community banks played in the U.S. economy during the COVID-19 pandemic. The focus is the PPP lending program. Teams must propose a hypothesis that demonstrates the role community banks played during the pandemic and develop a data analytics model to test their hypothesis using Paycheck Protection Program (PPP) data from the Small Business Administration, CSBS and elsewhere.

Our hypothesis is that PPP lending via community banks may have had a different impact on local economies than PPP lending through other institutions. Community banks' business model, which emphasizes ongoing relationships with local business borrowers, may have made them particularly effective distributors of PPP loans. Our analysis finds this to be the case. PPP lending through community banks tended to have been more effective than PPP lending via larger institutions. Each dollar of PPP lending via community banks lead to a larger decline in unemployment in the county where the borrower was located. Our main finding might be explained by our two subsidiary findings. First, PPP loans extended by community banks were forgiven at a much higher rate than PPP loans extended by banks which were larger and less tied to a locality. Higher forgiveness rate indicates that businesses which borrowed from community banks used PPP loans to pay costs of business, particularly payroll costs, which kept employees on their payroll and off of unemployment. Second, community banks extended PPP loans quicker than non-community banks. This helped borrowers to keep their employees on the payroll and provided funds to local communities quicker in times of need. These findings provide new insights for regulatory and policymaking purposes and add value to stakeholders such as bankers, businesses, and the general public, etc.

We reach these conclusions via the following analytic methods. In the first step, we created a data set as the foundation of our analysis. We began with the PPP loans data provided by CSBS and the BLS unemployment rate from 2019 to 2021 by using STATA. Then, we assigned PPP loans value via county zip code in R. In addition, we analyzed aggregate data which illustrated in tables, including the different proportion of PPP loans in community banks and non-community banks, the forgiveness value of PPP loans in both kinds of banks, the changes and trend of unemployment rate among the whole county. Moreover, to demonstrate visualized and macroscopical pictures of the relationship between PPP loans approval amount, forgiveness amount in both community banks and non-community banks and unemployment rate, we produced seven maps of the USA mainland based on our data set by using STATA. Furthermore, we built four quantitative regression models to understand the numerical relationship of (1.) change in unemployment rate and total PPP loans value; (2.) change in unemployment rate and PPP loans value made by non-community banks; (3.) change in unemployment rate and PPP loans value made by community banks; (4.) change in unemployment rate versus non-community bank loan value and community bank loan value. Lastly, we made one line plot and two scatter plots by STATA to see the proportion of community banks PPP loans lending in all PPP loans made by both kinds of banks overtime.

Community banks played an important role in PPP loans. Community banks gave quick, flexible and personal loans to local people and small businesses. Furthermore, community banks helped to adjust the unemployment rate in a positive way. From our mapping result, if the place has a high unemployment rate, it will also have a high use of PPP loans. The relationship between the unemployment rate and PPP loans are all positive in results and regression lines in both community bank figures and commercial bank figures, but community banks have a

stronger result than commercial banks, which means that community banks give more help for unemployed people than commercial banks. The results showed that when the PPP loans are going up, the unemployment rate will go down. We also find that the forgiveness of loans has a high rate in community banks, this means that community banks accept people who don't pay back their loans and this does increase the rate of the economic growth.

We substantiate our findings in the remainder of this essay. Section 2 reviews the current literature on PPP lending. Section 3 provides background information necessary to understand our arguments and statistical methods. Key information includes a description of the COVID-19 pandemic and its economic effects in the United States, details of the Paycheck Protection Program (PPP), and a description of community banks focussing on their characteristics and unique features. Section 4 presents the methods that we use to analyze the data, and the result we got from it.

2. Literature Review

In response to the negative effect of COVID-19 on economic conditions, policy makers of the U.S. federal government passed the Coronavirus Aid, Relief, and Economic Security Act (CARES Act) on March 27, 2020. That act establishes the Paycheck Protection Program (PPP) as a way of providing loans to support small business owners and offsetting revenue loss during business shutdowns. Existing studies about the Paycheck Protection Program mainly explore its impact on the job market and banking system. Providing a comprehensive assessment of financial intermediation and the economic effects of the Paycheck Protection Program (PPP), Granja, J., Makridis, C., Yannelis, C., & Zwick, E. (2020) reveal that banks played an important role in mediating program targeting, which helps explain why some funds initially flowed to regions that were less adversely affected by the pandemic. In another literature, Kapinos, P.

(2021) uses U.S. county-level data to study county-Level determinants and effect on unemployment. By focusing on the major goal of this program, some literatures began to investigate whether it is effective for boosting the economy and avoiding related issues of COVID-19 pandemic. To indicate the overall effectiveness of the program, Sabasteanski, N., Brooks, J., & Chandler, T. (2021) explore the types of business that received PPP funding, the ranges of loan amounts provided, the types of banks that processed the loans, the cost-effectiveness of jobs saved based on the loan range, and the racial distribution of loan recipients. In a more specific way, Allen, K. D., & Whitledge, M. D. (2021) analyzes the effectiveness of Paycheck Protection Program (PPP) for small business lending of loans of $150,000 or less using Google mobility data.

Among these literatures, few of them analyze the role of community banks to local businesses. To determine whether the impact of community differs from other banks in Paycheck Protection Program, our paper examines the relationship between community banks and local businesses by developing hypotheses and creating analytics models based on the PPP loan data. In terms of database, Barraza, S., Rossi, M., & Yeager, T. J. (2020) collect monthly county-level labor data through April 2020 from the Bureau of Labor Statistics to study the short-term causal effect of the Paycheck Protection Program on unemployment. In addition to the county level unemployment data, this paper draws FDIC (Federal Deposit Insurance Corporation) data to show areas with more community banks and match PPP loan data by zip code to reveal geographic distribution of PPP funds across U.S. counties. In terms of research method and model, Marsh, W. B., & Sharma, P. (2021) study bank responses to the Paycheck Protection Program (PPP) and its effects on lender balance sheets and profitability through a Bayesian joint model that examines the decision to participate. Given our assumption that the distribution of

community banks was exogenous to the COVID-19 Pandemic and the PPP lending program, our paper builds a panel regression with difference-in-difference estimators to show the influence of PPP lending from community banks compared to other banks on the local economy.

3. Background

3.1 COVID-19 Pandemic

The new respiratory illness starts to spread at the end of year 2019, it is known as Coronavirus disease or COVID-19. COVID 19 had a very strong contagious disease, with a very high incubation period and mortality rate. The virus tends to lie dormant in a person's body for 2 to 4 weeks long, and followed by symptoms such as cough, fever, difficulty breathing, muscle aches, headache, loss of taste and smell etc. Elder people and people who have compromised immune systems are more likely to have risk in COVID 19. The mode of transmission is through close contact, and viral particles are spread in poorly ventilated or crowded rooms. To slow and stop the quick spread of COVID 19, several countries like China, Korea, Italy, and Iran imposed major restrictions on travel, work and import and export. The government advises people who have symptoms to stay at home and calls on everyone to wear face masks to prevent close contact. But these moves have had little success, COVID 19 cases surged millions of people over the next few months in different places all over the world, and the number is counting. At the same time, due to the insufficient understanding of the new crown, there is no way to develop an effective vaccine in a short period of time. The surge in the COVID 19 had led to increased pressure on hospitals for treatment. Hospitals in various countries were full and insufficient of beds for those critically ill patients. Furthermore, since the COVID-19 Pandemic broke out suddenly, hospitals did not have extra time to purchase and collect medical materials, the medical

staff were insufficient, and the long working hours made those medical staff tired, etc. These were all the reasons that caused several places' medical systems to be on the verge of collapse.

The long-standing COVID-19 pandemic has not only affected people's basic lives, but also directly affected the economic markets of some countries, such as Italy, the United States, Spain, China, etc. Since the government asked people to stay at home to avoid close contact, the industrial chain of stores, companies, production lines, etc., has been shut down for a while, and this status has continued for a long period of time. It is easy to understand that this kind of situation will cause the GDP decline quickly, since the calculation of GDP=CA+I+CB+X. Where "CA" is consumption, "I" is Private investment, "CB" is government spending, and "X" is net exports. Also if no one consumes anything in the past several months, the number of consumption will get lower compared to the day before. Not to mention that not only the consumption is getting lower, the net exports are also decreasing at the same time due to the closure of ports.

3.2 Paycheck Protection Program Loans

In order to reduce the impact of COVID-19, the US government began to reduce economic activities in March 2020. A large proportion of the small businesses stopped working or temporarily closed since then. This caused overall employment to increase significantly. To be more specific, the unemployment rate of the United States climbed from 4.4% to 14.7% from March 2020 to April 2020 according to BLS, which rose to record high. The unemployment rate increased by 10.3% in only one month. If a large number of small businesses shut down, the economy would be hit, which might cause a series of serious consequences. One of these is that the public loses confidence in the US economy.

In this case, the federal government needed to take some appropriate actions. The Paycheck Protection Program, henceforth PPP, is an SBA (U.S. Small Businesses Administration)-backed loan that helps businesses keep their workforce employed during the COVID-19 crisis. PPP loans aim to help small businesses cover their usual expenses like payroll costs and other eligible costs to get through this difficult time. Under this circumstance, workers can stay at home without working and meanwhile the economy can function relatively well.

In addition, to encourage the small business owner to spend most part of PPP loans on their employees' salary, the act regulated that qualified borrowers may be eligible for PPP loan forgiveness. For example, for first draw PPP loans' lenders who satisfy that employee and compensation levels are maintained, the PPP loans proceeds are spent on payroll costs and other eligible expenses, and at least 60% of the proceeds are spent on payroll costs during the 8- to 24-week covered period, they are qualified for full loan forgiveness.

3.3 Community Banks

"Loan funds were disbursed by financial institutions including commercial banks, thrifts, credit unions, and fintechs. This mode of distribution mirrored the standard SBA loan programs that support small businesses and utilized the SBA's existing lender networks. That said, the loan terms, eligibility, and forgiveness conditions differed substantially from existing SBA loan programs."(Marsh & Sharma, 2021)

Community banks are institutions that issue depositary and lending issues in small and certain geographic areas. They are owned and operated by commercial institutions and they spread over the whole country as the foundation or basis of cities and towns. The primary customers for community banks are local individuals and small businesses. As a result, individuals can easily find several community banks, for example Carver Bank, Ally Bank,

Bankers Trust etc., near their current locations. Since community banks only serve for certain locations, they are more specialized in specific regions than bigger banks. In other words, they are effective lenders because they have knowledge of borrowers in their areas. They know more about their neighborhood and local economy and cultures.

Community banks value customers' personal relationships like family history to decide whether to make a loan or not, the loan issued, the interest rate and so on. In contrast, big commercial banks tend to evaluate their customers using standard criteria such as credit scores, earnings, assets etc. The knowledge that community banks have of their local customers are their advantages compared to large national banks. These advantages rendered PPP loans functioned at a quicker speed and further overcome the economic fallout during the covid-19 pandemic.

Community banks contribute a lot in Paycheck Protection Program lending. Yosif, N. (2021) pointed out that community banks made 60 percent of all PPP loans—including 72 percent of PPP loans to minority businesses. Moreover, community banks put more effort on vulnerable businesses in the period of pandemic by "accounting[ing] for 67 percent of PPP loans to industries with average hourly earnings of $10 to $20 per hour. They also accounted for over 50 percent of all PPP loans to industries with average hourly earnings between $20 and $50 per hour." In addition, community banks play a much more important role in rural and suburban communities than in cities by "accounting for 85 percent and 72 percent of all PPP loans, respectively—while accounting for 51 percent of PPP loans in urban communities."

4. Method and Results

4.1 Data Sources

The data sources we used for this project include PPP loan-level data, 2020 and current unemployment data, US county names and FIPS codes, and NAICS codes for industries. The PPP loan-level data was provided by CSBS for the 2022 Data Analytics Competition. We collected the unemployment data from the Bureau of Labor Statistics (BLS). Our table of US county names and FIPS codes comes from the US Department of Agriculture (USDA). Finally, we received a table matching two-digit NAICS codes to their respective industries from the Census Bureau. Along with collecting these data sources, we also merged and transformed the data in order to create the models and figures we used in this paper. These transformations will be covered in the following paragraphs.

First, we will address the modifications made to the PPP loan-level dataset. We began by assigning each loan in the PPP loan-level dataset a county FIPS code based on the county of the loan borrower. We chose to use FIPS codes in order to give each loan a unique county ID, which would not have been possible using county name alone. Additionally, using county and state name would not be as efficient as a FIPS code, due to the fact that different datasets have different standards for capitalizing or combining the county and state names. FIPS assignment was done by matching the county and state names to the respective FIPS code using the table from the USDA. Using the FIPS codes, we aggregated the total loan values (*currentapprovalamount*), the total dollars forgiven (*forgivenessamount*), and the number of jobs reported (*jobsreported*) by borrower country. We also tallied each of the previously mentioned statistics based on community bank status. These variables are represented by a suffix "_cb" or

"_ncb" for community bank and non-community bank respectively. We calculated the total

forgiveness rate (*forgivenessrate*) using the formula in Equation 1.

Equation 1:

$$forgivenessrate \ = \ \frac{forgivenessamount}{currentapprovalamount}$$

For CB and NCB, we modified Equation 1 to use the "_cb" and "_ncb" versions of the variables.

The next dataset that we made modifications to was the unemployment data from the

BLS. Originally, the data we collected included the 2020 yearly average unemployment rate, as

well as a monthly average unemployment rate for the months from December 2020 to January

2022. At the time of our analysis, the BLS did not publish the yearly average unemployment rate

for 2021. Instead, we used the monthly averages for the months of 2021 to calculate this figure

ourselves. From there, we merged the unemployment data with our PPP loan-level data via the

borrower county FIPS code. Then, we calculated the change in unemployment rate using the

formula in Equation 2.

Equation 2:

$$\Delta Unemployment \ = \ Unemployment_{2021} \ - \ Unemployment_{2020}$$

In Equation 2, the *Unemployment* variables represent the yearly average unemployment rate,

with the subscript indicating the year.

The other datasets we used were not modified for this analysis.

4.2 Mapping Analysis

We began our analysis by mapping sets of variables from our datasets by US county. In total, there are seven maps drawn for the following: (1.) Change in the unemployment rate from 2020 to 2021; (2.) Current approval amount of Total PPP loans value made by banks; (3.) Current approval amount of PPP loans value made by community banks; (4.) Current approval amount of PPP loans value made by non-community banks; (5.) Forgiveness rate for total PPP loans made by banks; (6.) Forgiveness rate for PPP loans made by community banks; (7.) Forgiveness rate for PPP loans made by non-community banks. These maps clearly show how PPP loans are disbursed by geographic location and how PPP loans are related to unemployment.

There are three patterns found from the seven maps. One, PPP lending is negatively correlated with changes in unemployment by county in 2020-2021. This correlation means that in counties that receive more PPP lending the unemployment rate recovered more quickly after the peak of the covid pandemic. Lighter regions on the map of the change in unemployment by county indicate larger decreases in unemployment. However, those regions are darker on the map of the current approval amount and the forgiveness amount for both community banks and non-community banks. Inverse colors show that PPP loans helped small businesses maintain job positions, and thus decreased the unemployment rate from 2020 to 2021.

Two, more PPP loans were borrowed on the east and west coasts. Most darker regions are located on the east and west coasts, which means that more small businesses were operating in those areas. Larger amounts of current approval from banks helped them overcome the recession caused by COVID-19. The midlands have not been affected as much as the east and west coasts. And thus the PPP loans approval value is lighter in middle regions. This pattern stays true for PPP loans made by both community banks and non-community banks.

Three, the forgiveness rate for total PPP loans was higher in the midland of the United States. Although businesses from midland borrowed less PPP loans than those from east and west coasts, the money they received from PPP loans was mainly put in payroll costs. According to the SBA, businesses or individuals that spend at least 60% of their total loan on payroll costs will receive full forgiveness over the 8- to 24-week covered period. This illustrates that those darker regions remark businesses on the midland paid most of the PPP loans in employee's salaries in order to improve workers' life situation. Again, this pattern is true for PPP loans made by both community banks and non-community banks.

4.3 Regression Analysis

After noting the negative correlation between community bank (CB) PPP lending and change in unemployment, we constructed a series of simple linear regressions to quantify the nature of this relationship. In total, we developed four linear models: (1.) Change in Unemployment from 2020 to 2021 regressed against Total Lending Amount, (2) Change in Unemployment from 2020 to 2021 regressed against Lending Amount by CB, (3) Change in Unemployment from 2020 to 2021 regressed against Lending Amount by non-Community Banks (NCB), and (4) Change in Unemployment from 2020 to 2021 regressed against Lending Amount by CB and Lending Amount by NCB. In all of these models, the lending amount was measured in billions of dollars. Using the variable definitions from Section 4.3, we define the variable *Lending* as is shown in Equation 3.

Equation 3:

$$Lending = \frac{currentapprovalamount}{10^9}$$

The variables *CBLending* and *NCBLending* are defined similarly, with *currentapprovalamount* being replaced by *currentapprovalamount_cb* and *currentapprovalamount_ncb* respectively.

Our first model, shown in Equation 4, was used to ascertain whether or not there was a significant relationship between the amount of PPP lending and the change in unemployment. Equation 4:

$$\hat{y} \ = \ \beta_0 \ + \ \beta_1(Lending) \ + \ \varepsilon$$

Based on the results shown in Table 1, it is clear that these variables have a significant relationship. Expanding on this result, we can see that in models 2 and 3, represented by Equations 5 and 6 respectively, the relationship between dollars loaned and change in unemployment continues even after filtering for a certain bank type (CB or NCB).

Equation 5:

$$\hat{y} \ = \ \beta_0 \ + \ \beta_1(CBLending) \ + \ \varepsilon$$

Equation 6:

$$\hat{y} \ = \ \beta_0 \ + \ \beta_1(NCBLending) \ + \ \varepsilon$$

In particular, Table 1 shows us that the coefficient in model 2 is larger than the coefficients of model 1 or model 3. This seems to indicate that CB lending has a larger impact on decreasing the unemployment rate than NCB or aggregate lending.

We continued our regression analysis with model 4, which places both CB and NCB lending in one model (see Equation 7).

Equation 7:

$$\hat{y} \ = \ \beta_0 \ + \ \beta_1(CBLending) \ + \ \beta_2(NCBLending) \ + \ \varepsilon$$

The exact coefficients given in Table 1 for this model may not be completely accurate. CB lending and NCB lending are highly correlated variables, leading to collinearity within the model. In this case, the coefficients are biased towards 0 and the standard errors are biased upwards. However, despite these biases, it is clear that CB lending has a larger effect on the change in unemployment rate than NCB lending does.

4.4 Robustness Checks:

In order to test the robustness of our regression analysis, we calculated a few more tables that measure the impact of community bank lending. First, we calculated the percentage of PPP loans that were forgiven by community and non-community banks. The results are shown in Table 2. We found that community banks were much more likely to offer loan forgiveness to small businesses than non-community banks. This trend holds true whether the percentage of forgiven loans is calculated based on the number of loans issued, or the total value of loans issued. PPP loan forgiveness is highly correlated with lower unemployment rates. This is due to the criteria that businesses need to meet in order to have their loans forgiven. Specifically, a business can have their PPP loan forgiven if they use the funds of that loan to pay their employees. These employees are then able to keep their job instead of collecting unemployment insurance. With this information in mind, the results in Table 2 seem to firmly support the results implied by our regression analysis.

Along with the percentages of forgiven loans, we also looked at the distribution of loans across various industries. Using the NAICS codes provided by CSBS, we tallied up the number of loans distributed and the total value of those loans by industry and by bank type. We found that in all industries aside from agriculture, NCB loans outnumbered CB ones. The other industry where the gap between CB and NCB lending was small was the mining industry. Interestingly,

both of these industries tend to be clustered in rural areas of the country. This presents the question of whether it was CB lending that led to falling unemployment rates, or if rural communities were quick to recover from the pandemic for other reasons. For instance, it is possible that rural regions managed to avoid large spikes in COVID cases due to their low population densities. Originally, we were planning to investigate this issue using the County Business Patterns (CBP) data from the Census Bureau. However, as of April 20, 2022, CBP data for 2020 has yet to be published.

4.5 Loan Timing

The timing data are sorted from PPP loan data provided by CSBS. The dataset clearly recorded the date of loan lending, the amount of PPP loans made by all banks and community banks, borrowers' names, and their counties. Using the date of loan lending, we collapsed the sum of PPP loans by date and assign data to two categories: all banks and community banks.

With the data collapsed by date, we drew a set of three graphs. Figure 8 is the count of loans issued of PPP loans by all banks and by community Banks. The time period is set for the first draw of PPP loans from April to September of 2020. The blue line represents the total PPP loan times made by all banks and the red line represents the PPP loans times made by community banks. This figure gives us a picture of how many community banks issued PPP loans by date compared to all issuing banks.

We also calculated the proportion of PPP loans made by community banks. The formula for this proportion is the number of PPP loans made by community banks divided by the total number of PPP loans made by all banks. For the scatter plots in Figure 9 and Figure 10, we only included the percent of PPP loans made by community banks on weekdays. The aim was to

avoid outliers, as only non-community banks made loans on weekends. The scatter plots are lucid to show how many PPP loans were made by community banks on each issuing day. Figure 9 and figure 10 demonstrate that the proportion of PPP loans extended by community banks for the first draw and the second draw of PPP loans.

Figure 8 shows counts for PPP loans made by all banks and by community banks. One finding from this line graph is that PPP loans made by all banks had a peak up to 800,000 counts and PPP loans made by community banks had a peak up to 180,000 counts around May 1, 2020. Most PPP loans were made by both kinds of banks three months after the outbreak of COVID-19. According to U.S. Bureau of Labor Statistics Data, the unemployment rate decreased after April 2020. PPP loans might also contribute to this decline, helping businesses pay wages and keep their businesses afloat. Furthermore, non-community banks issued PPP loans much more times and higher loan value than community banks, but community banks always took action at a higher speed. The peak of counts for community banks' lending times was earlier than the peak of total counts for both kinds of banks.

Figure 9, the proportion of PPP loans extended by community banks, reached its peak in April 2020, which is the very beginning time of the first draw of PPP loans. Then, the percent of PPP loans issued by community banks declined as time went by and kept stable around approximately 20%. The proportion of PPP loans made by community banks was over 80% in the first week and over 50% in the following couple of weeks. This means that community banks acted very rapidly in assigning loans to local small businesses and individuals in the first few weeks of PPP loans acts implementation. The first spot in the scatter plot shows that only less than 20% of PPP loans disbursed by large banks indicates that community banks were much more helpful than non-community banks when the PPP loans act came into the effort. But here

we are not sure about the reason. Did community banks know more about their customers so that they could better serve clients compared to big banks? Or did community banks have stronger incentives to take action to assign PPP loans? Or did smaller community banks have less processes than large banks so they could distribute loans quicker? To figure out these questions, we need more information provided by the CSBS team.

Figure 10 shows the trendency when the second draw PPP loans implemented. Around January 2021, the COVID-19 situation in the US became very severe. Reported cases boomed in late January and early February 2021. During this time, the proportion of PPP loans made by community banks first increase to over 75% (peak) in late January and then kept descending overtime. Community banks reacted very sensitively to the second PPP loans acts which are determined by covid situation. These loans helped employees who tested positive and who needed to work from home overcome their difficult time and prevented them losing their jobs. In contrast, non-community banks reacted to the second PPP loans much slower.

5. Reference

Allen, K. D., & Whitledge, M. D. (2021). Further evidence on the effectiveness of community banks in the Paycheck Protection Program. Finance Research Letters, 102583.

Barraza, S., Rossi, M., & Yeager, T. J. (2020). The short-term effect of the Paycheck Protection Program on unemployment. Available at SSRN 3667431.

Granja, J., Makridis, C., Yannelis, C., & Zwick, E. (2020). Did the Paycheck Protection Program hit the target? (No. w27095). National Bureau of Economic Research.

Kapinos, P. (2021). Paycheck protection program: County-level determinants and effect on unemployment.

Marsh, W. B., & Sharma, P. (2021). Government loan guarantees during a crisis: The effect of the PPP on bank lending and profitability. Federal Reserve Bank of Kansas City Working Paper, (21-03).

Sabasteanski, N., Brooks, J., & Chandler, T. (2021). Saving lives and livelihoods: The Paycheck Protection Program and its efficacy. EconomiA, 22(3), 278-290.

Yosif, N. (2021). PPP data show community banks served those most in need. Default. Retrieved April 21, 2022, from
https://www.icba.org/newsroom/blogs/main-street-matters/2021/11/10/paycheck-protection-program-data-show-community-banks-served-those-most-in-need

6. Figures and Tables

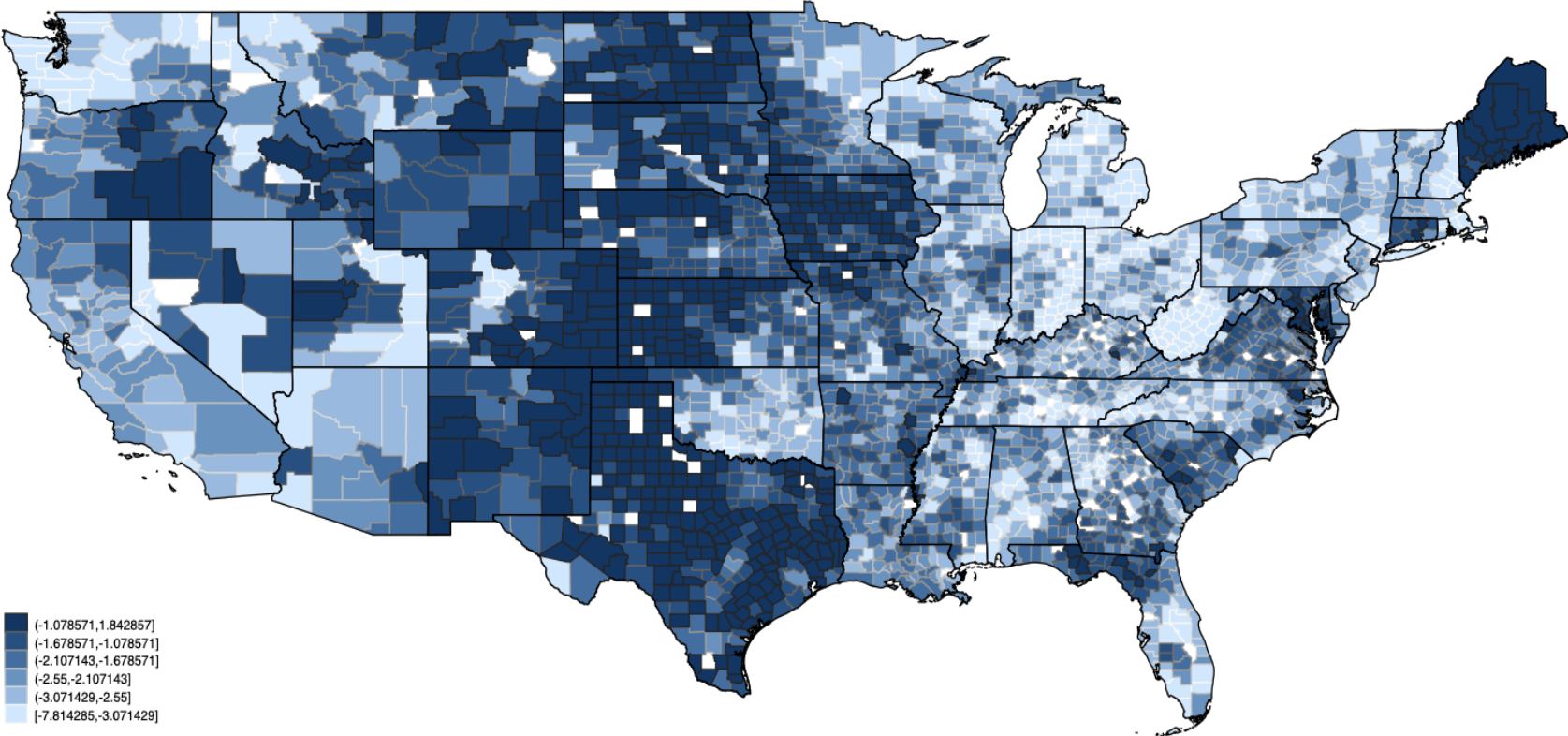**Figure 1: Change in Unemployment Rate by County 2020-2021**

(-1.078571,1.842857]
(-1.678571,-1.078571]
(-2.107143,-1.678571]
(-2.55,-2.107143]
(-3.071429,-2.55]
[-7.814285,-3.071429]

Figure 2: Current Approval Amount for Total PPP Loans

(1.64e+08,1.87e+10]
(6.14e+07,1.64e+08]
(2.77e+07,6.14e+07]
(1.35e+07,2.77e+07]
(4900422,1.35e+07]
[1083,4900422]
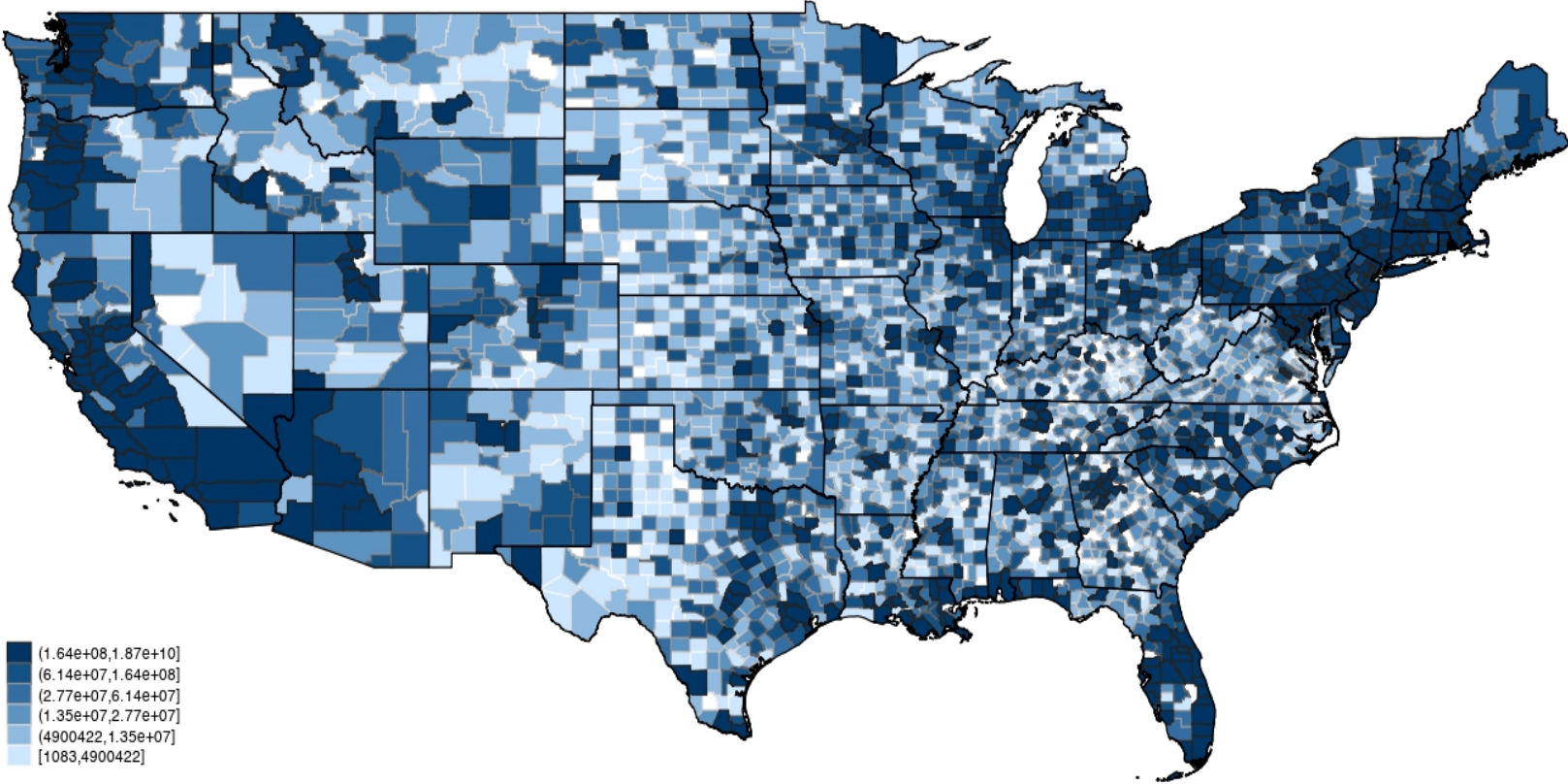
Figure 3: Current Approval Amount for PPP Loans by Community Bank

(6.67e+07,2.63e+09]
(2.91e+07,6.67e+07]
(1.47e+07,2.91e+07]
(6896426,1.47e+07]
(2482450,6896426]
[1083,2482450]
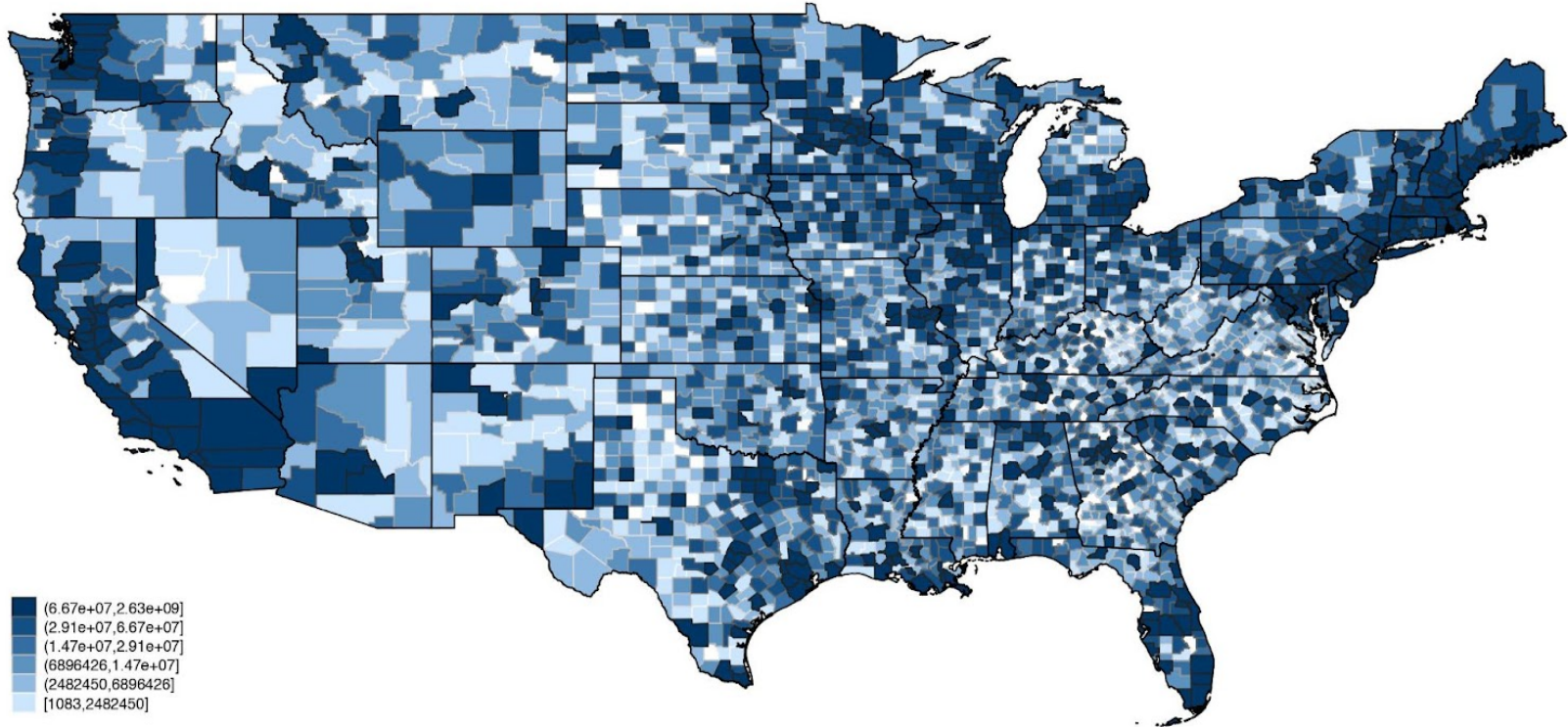
Figure 4: Current Approval Amount for PPP Loans by Non-community Bank

Legend:
- (9.80e+07,1.61e+10]
- (2.77e+07,9.80e+07]
- (1.06e+07,2.77e+07]
- (3820954,1.06e+07]
- (1016130,3820954]
- [0,1016130]
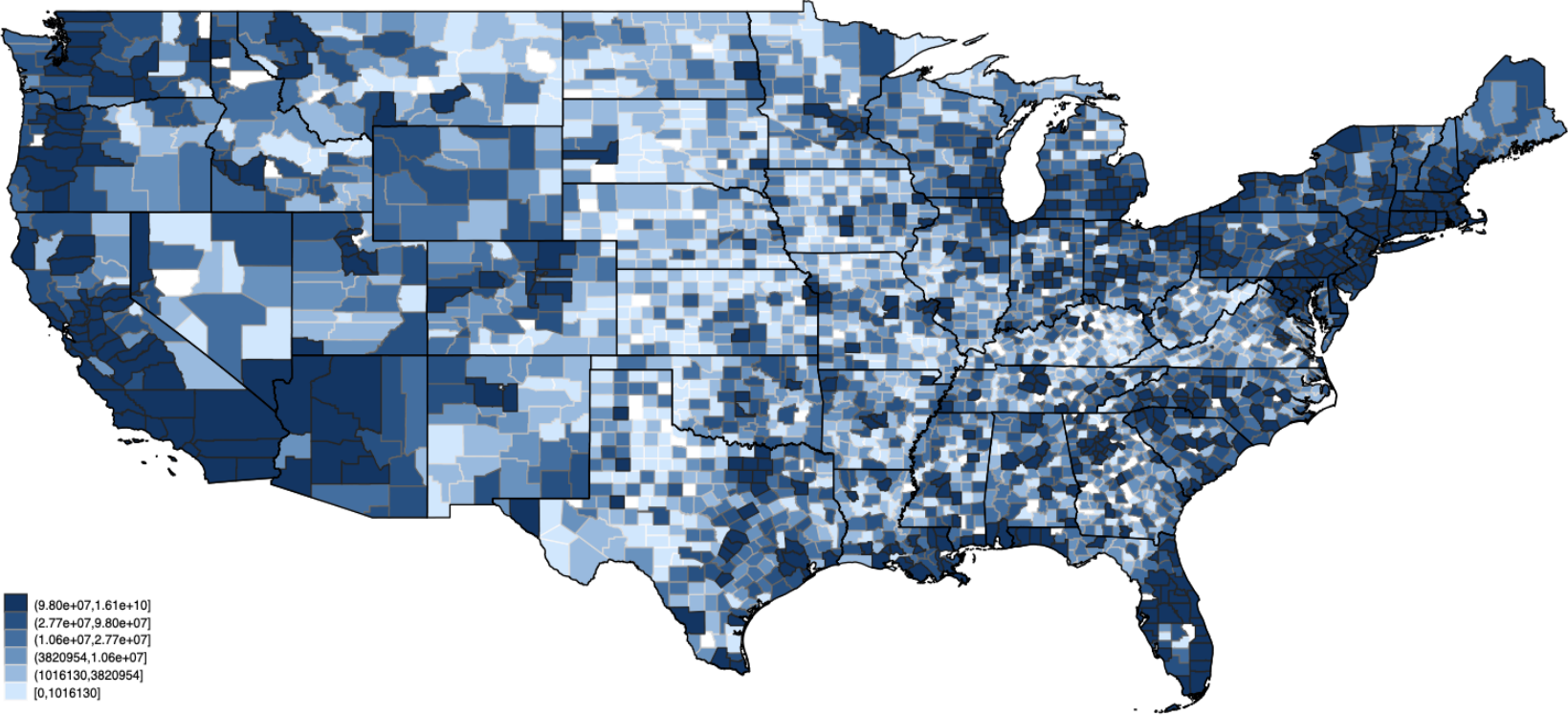
Figure 5: Forgiveness Rate for Total PPP Loans

Legend:
- (.8224384,1.011062]
- (.7684626,.8224384]
- (.7239332,.7684626]
- (.672525,.7239332]
- (.5980296,.672525]
- [0,.5980296]
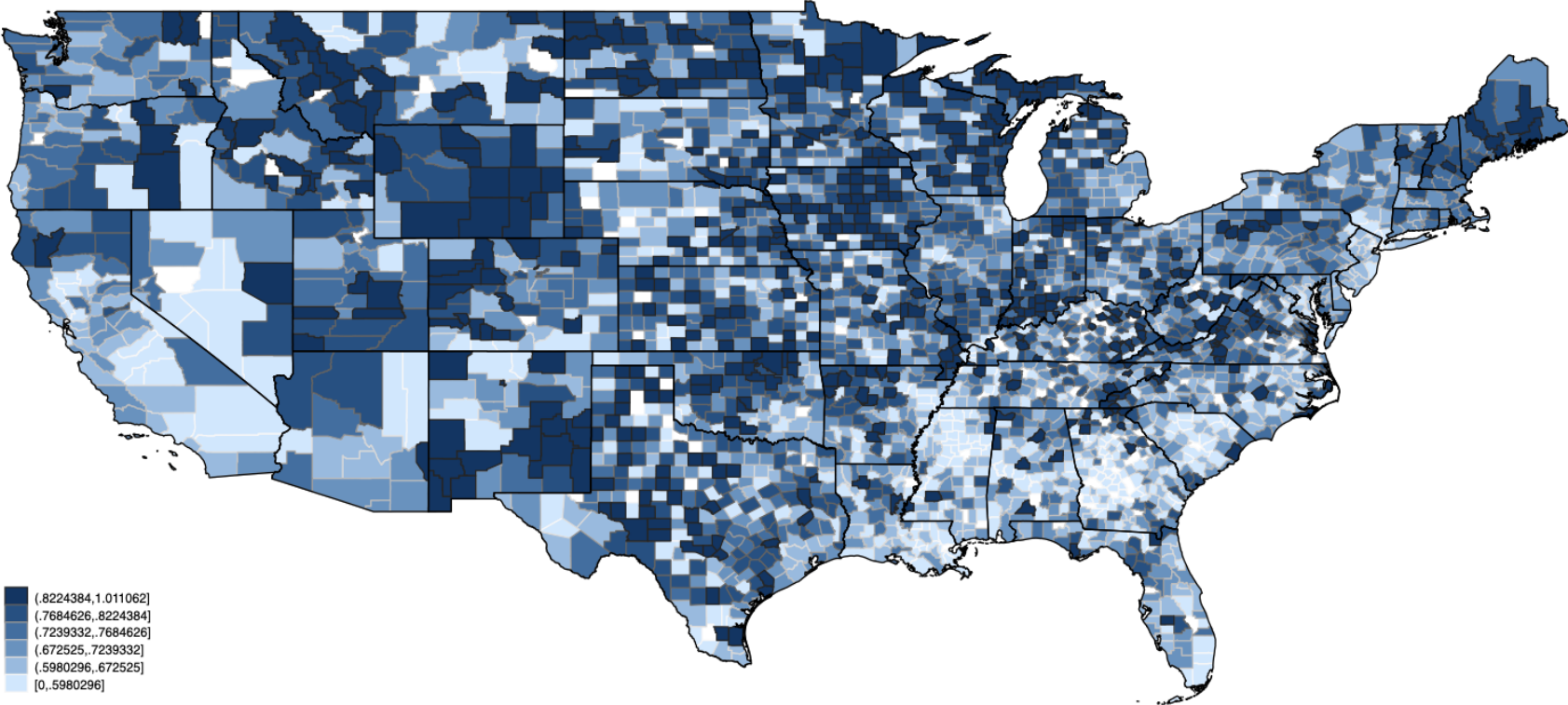
Figure 6: Forgiveness Rate for PPP Loans by Community Bank

(.8776697,1.011339]
(.8329937,.8776697]
(.7888363,.8329937]
(.7372392,.7888363]
(.6530313,.7372392]
[0,.6530313]
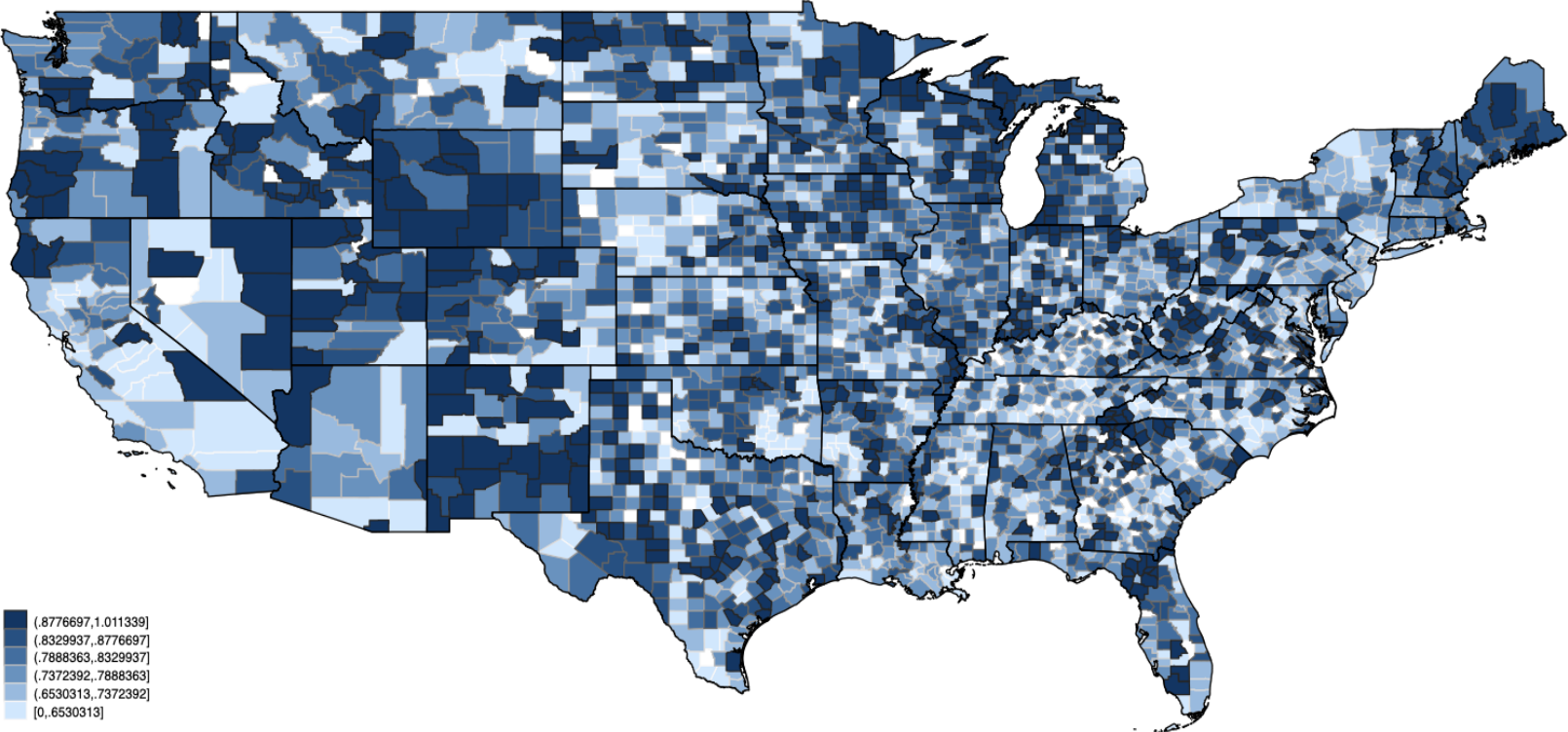
Figure 7: Forgiveness Rate for PPP Loans by Non-community Bank

(.7871581,1.009836]
(.7081469,.7871581]
(.6492102,.7081469]
(.565155,.6492102]
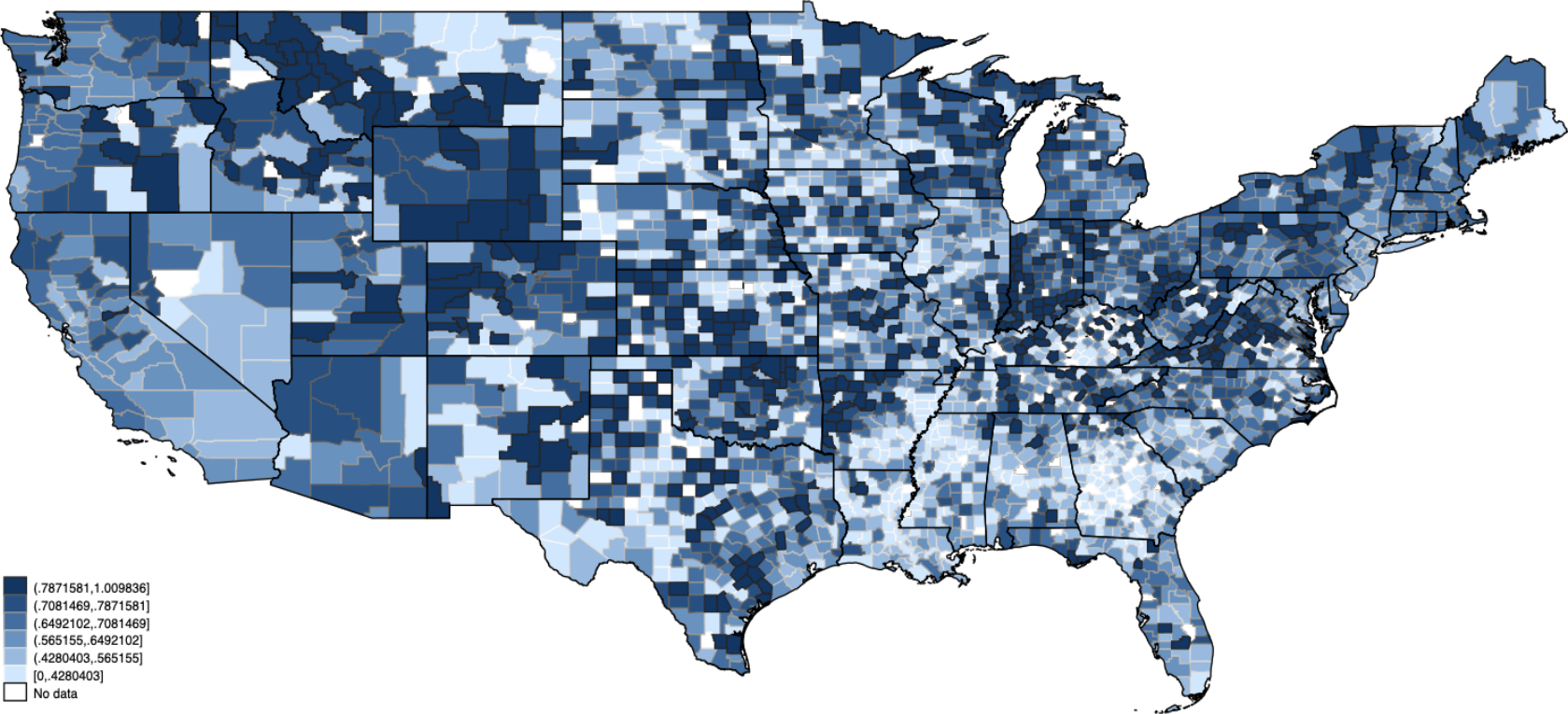(.4280403,.565155]
[0,.4280403]
No data

Figure 8: Counts for PPP Loans Made by All Banks and PPP Loans by Community Banks
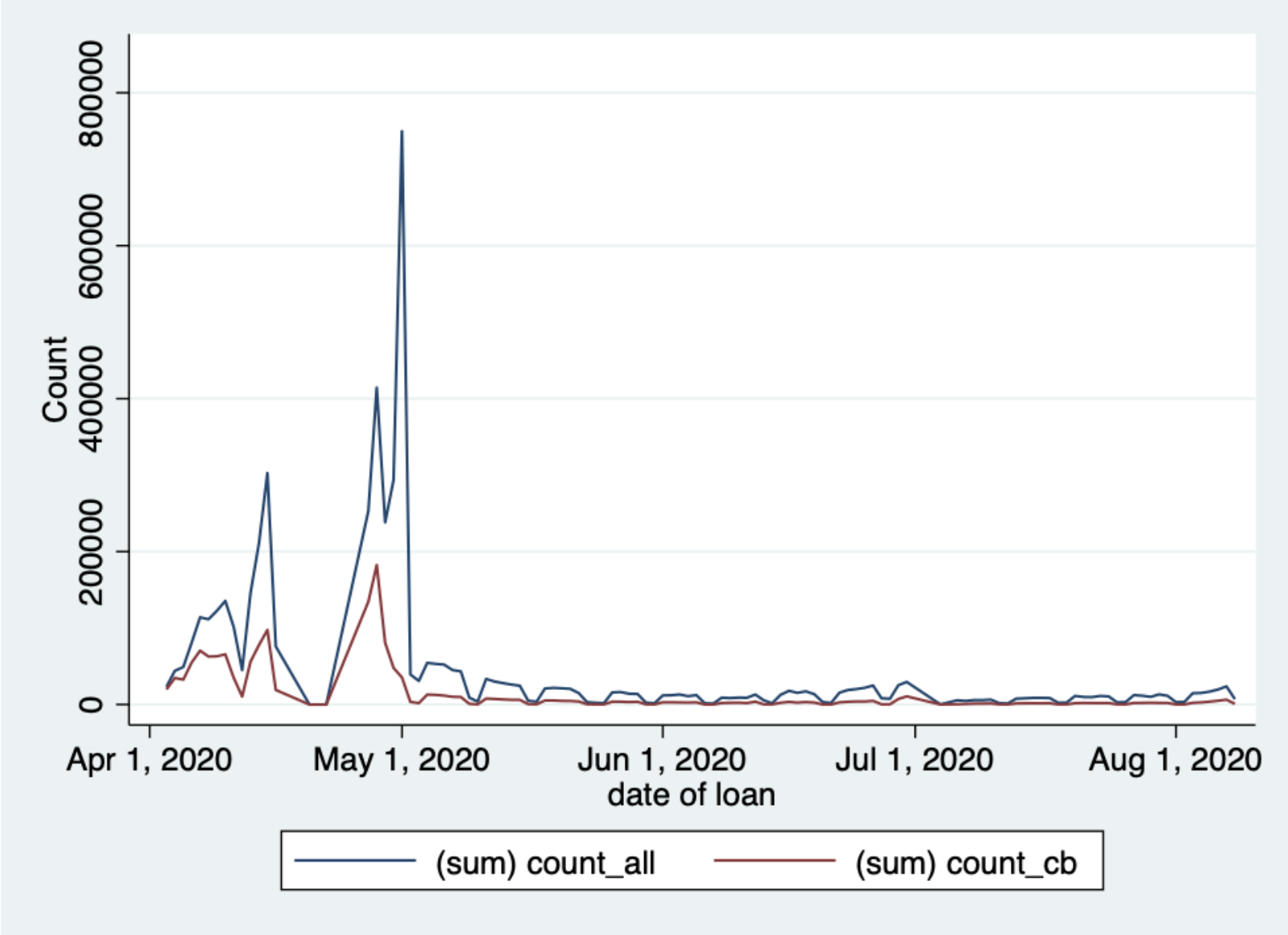
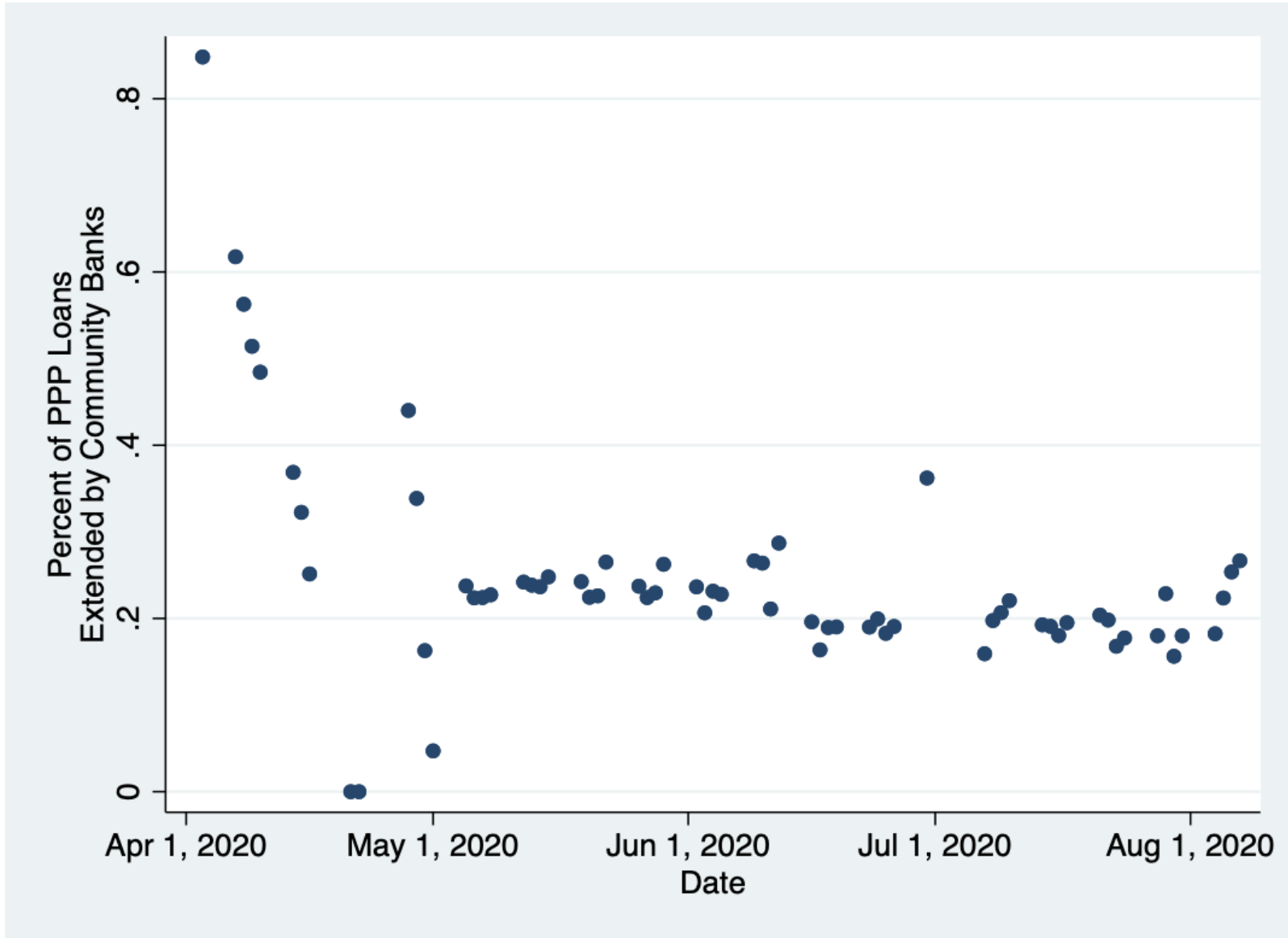**Figure 9: Percent of PPP Loans Extended by Community Banks in 2020**

Figure 10: Percent of PPP Loans Extended by Community Banks in 2021
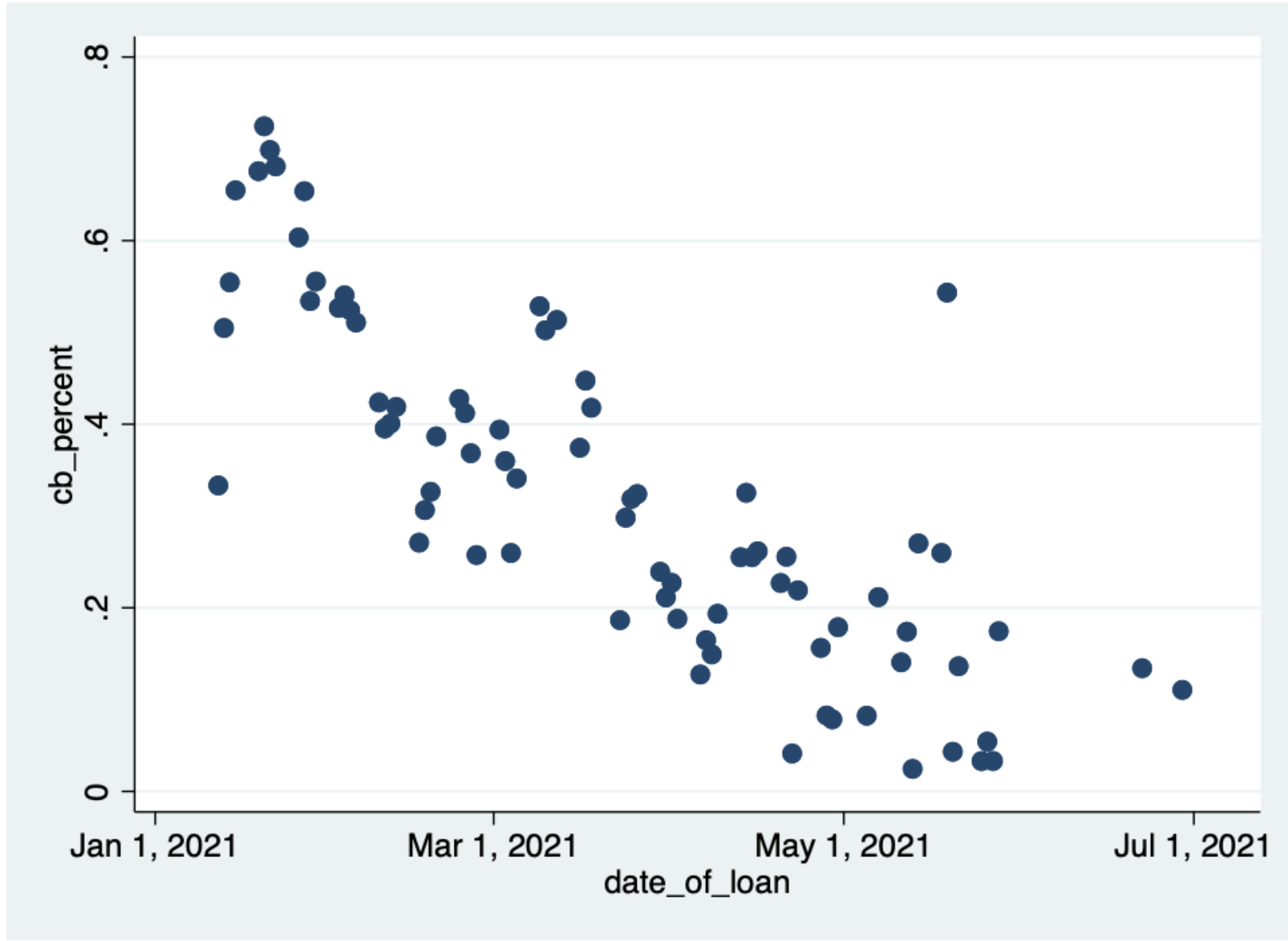
Table 1 : Regression Results

Variables	All Loans (1)	Only CB (2)	Only Non-CB (3)	CB and Non-CB (4)
Total PPP Loans ($ bil)	-0.19935 *** (0.028)			
Community Bank PPP Loans ($ bil)		-0.98143*** (0.136)		-0.61270 * (0.259)
Non-Community Bank PPP Loans ($ bil)			-0.23560 *** (0.0335)	-0.10672 . (0.06402)

Notes: Standard error in parenthesis. Significance level indicated by *** - 0.001, ** - 0.01, * - 0.05, . - 0.1.

Table 2: Percentage of Loans Forgiven by Bank Type

Bank Type	# All Loans (mil)	# Forgiven (mil)	Percent		Total Value ($ mil)	Forgiven Value ($ mil)	Percent
		Forgiven By Number					**Forgiven By Value**
Community	2.3	1.4	61.5%		561,155	126,992	77.3%
Non-Community	6.1	2.4	38.8%		396,902	242,730	61.2%
All	8.4	3.8	45%		164,253	369,722	65.9%

Table 3: Loans Distributed by Industry and Bank Type

NAICS Code	Industry Title	# Businesses (mil)	# CB Loans (10k)	# NCB Loans (10k)	# All Loans (10k)	CB Loan Value ($ bil)	NCB Loan Value ($ bil)	All Loan Value ($ bil)	% cb Loans (Count)	% cb Loans (Value)
23	Construction	1.51	24.75	50.53	75.28	23.36	44.05	67.41	32.9	34.7
11	Agriculture, Forestry, Fishing and Hunting	3.68	39.25	14.83	54.08	7.66	5.96	13.62	72.6	56.2
72	Accommodation and Food Services	9.00	15.17	37.00	52.17	14.48	29.56	44.03	29.1	32.9
21	Mining	.032	1.43	1.51	2.94	1.94	2.71	4.65	48.5	41.8
42	Wholesale Trade	.70	5.68	1.97	25.42	6.81	20.93	27.73	22.4	24.5
54	Professional, Scientific, and Technical Services	2.41	21.43	69.05	90.48	17.64	50.69	68.32	23.7	25.8
81	Other Services (except Public Administration)	1.92	25.85	97.02	122.87	10.63	31.21	41.84	21	25.4
52	Finance and Insurance	.77	6.74	16.41	23.15	3.88	8.59	12.47	29.1	31.1
92	Public Administration	.26	.59	1.65	2.24	0.62	1.25	1.88	26.4	33.2
62	Health Care and Social Assistance	1.70	17.30	51.26	68.54	21.72	48.17	69.88	25.2	31.1

56	Administrative and Support and Waste Management and Remediation Services	1.65	9.71	37.89	47.60	7.07	21.96	29.03	20.4	24.3
61	Educational Services	.43	2.66	9.78	12.43	3.54	8.78	12.32	21.4	28.8
53	Real Estate Rental and Leasing	.89	11.57	25.96	37.53	5.04	11.68	16.72	30.8	30.1
71	Arts, Entertainment, and Recreation	.38	5.04	18.85	23.89	2.50	7.21	9.71	21.1	25.8
51	Information	.37	1.97	8.08	10.06	2.12	7.55	9.67	19.6	21.9
22	Utilities	.05	.34	.71	1.05	0.55	0.88	1.43	32.2	38.7
55	Management of Companies and Enterprises	.08	.21	.95	1.16	0.37	1.15	1.51	17.9	24.2