CSBS 2022 Annual Data Analytics Competition

A Study of Community Bank-originated PPP Loans on Bankruptcy Rates

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Abstract

Studies have suggested that, in times of economic crisis, capital-rich large companies weather the storm better than small businesses. The COVID-19 pandemic crisis is no different in terms of damage to the economy. On top of the Federal Reserve's various monetary policies that injected massive liquidity into the wide financial system[1], the Small Business Administration (SBA) has devised another financial policy, Payroll Protection Program (PPP), that specifically targets American small businesses.

Community banks (CBs) have played a significant role in distributing PPP, with evidence from the full set of PPP loan data from SBA and bankruptcy filings data from Bankruptcy Courts, community banks, in general, serve small businesses in communities that are more prone to bankruptcy. Given the payroll nature of the PPP, counties with more PPP loans originated by community banks are associated with a lower level of cases of bankruptcy (business and non-business) filings during the Covid-19 pandemic. However, using a rolling window regression, such an association diminishes over time, suggesting the policy effectiveness of PPP could be short-lived but played the role of deferring bankruptcy.

Despite the dwindling number of community banks over the years, the regulators shall pay close attention to the significant financial intermediary roles that community banks are capable of playing in times of economic and financial crisis.

[1] "What did the Fed do in response to the COVID-19 crisis?" Brookings Institution. https://www.brookings.edu/research/fed-response-to-covid19/

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I. Introduction

1) Paycheck Protection Program

As an economic stimulus measure, the Paycheck Protection Program (PPP) established by the Coronavirus Aid, Relief, and Economic Security (CARES) Act, was implemented by the Small Business Administration (SBA) with support from the Department of the Treasury[2]. PPP loan is designed to help small businesses in keeping their employees on payroll. This loan can be used to fund not only payroll costs but also mortgage interests and other operational expenses. However, PPP is a payroll-targeted loan: if at least 60% of the approved loan proceeds are spent on payroll costs, the loan is eligible for full loan forgiveness.

In this research, we analyze the First Draw PPP loans which refer to the PPP loans made to new borrowers who are applying for the first time. This first draw PPP loan is composed of two rounds:

- Round 1 Application Period: April 3, 2020[3] to August 8, 2020
- Round 2 Application Period: January 15, 2021[4] to May 31, 2021

Since approvals take time, the approval dates of PPP loans range from April 3, 2020 - June 29, 2021.

2) Community banks

Community banks have a close relationship with local businesses as their business operations are based on community-level[5]. Thus, they are well aware of the circumstances and the financial needs of the businesses in their area. Moreover, since they are more capable of making decisions quickly compared to larger banks, they were able to play an important role in the PPP implementation processes in the local communities[6].

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[2] U,S, Department of Treasury. "Paycheck Protection Program." Accessed on April 24, 2022. https://home.treasury.gov/policy-issues/coronavirus/assistance-for-small-businesses/paycheck-protection-program

[3] U.S. Small Business Association. "Press release: SBA and Treasury Release Paycheck Protection Program Loan Forgiveness Application." May 16, 2020. Accessed on April 24, 2022. https://www.sba.gov/article/2020/may/16/sba-treasury-release-paycheck-protection-program-loan-forgiveness-application

[4] U.S. Small Business Association. "Press release: SBA Re-Opening Paycheck Protection Program to Small Lenders on Friday, January 15 and All Lenders on Tuesday, January 19." January 13, 2021. Accessed on April 24, 2022. https://www.sba.gov/article/2021/jan/13/sba-re-opening-paycheck-protection-program-small-lenders-friday-january-15-all-lenders-tuesday

[5] Federal Deposit Insurance Corporation. "FDIC Community Banking Study." December 2020. https://www.fdic.gov/resources/community-banking/report/2020/2020-cbi-study-full.pdf

[6] CSBS. "Community Banks Play Outsized Role in PPP Lending." December 11, 2020. Accessed on April 24, 2022. https://www.csbs.org/newsroom/community-banks-play-outsized-role-ppp-lending

3) Hypothesis

In this research, we focus on the roles of community banks during the Covid-19 pandemic, especially in preventing bankruptcies in the communities they serve. Since community banks have more interaction and stronger ties with the local businesses compared to non-community banks[7], we hypothesize: communities with higher proportions of community bank-originated PPP loans have lower bankruptcy rates.

II. Datasets

1) PPP

We combined the full PPP loan dataset provided by the United States Small Business Administration (SBA)[8] and the PPP loan dataset by the Conference of State Bank Supervisors (CSBS)[9] to obtain the community bank indicator ("cb") and FDIC certificate number for the originating bank ("cert") as of January 2022. The combined data has a total count of 8,614,374 PPP loans in the first draw. Using the borrowers' locational information provided in PPP, we retrieved county information of each loan[10] and grouped loans by county. Then, we further computed the share of the number and the approval amount of PPP loans originated by community banks in each county. These variables are the variables of our main interest.

2) Bankruptcy

We used bankruptcy filings data (Table F-5A) provided by the United States Courts[11] as the dependent variable. This data allowed us to use county-level samples in different time periods. Since the data is updated and reported on a quarterly basis for the last 12-month period, the data contains four different periods after the implementation of PPP (April 2020 - March 2021, July 2020 - June 2021, October 2020 - September 2021, and January 2021 - December 2021). The limitation of the dataset is that it does not have monthly or quarterly data. Since only yearly data starting from the first day of every quarter is provided, we were not able to analyze the immediate effects of PPP loans on bankruptcy.

[7] Ibid.
[8] Available on https://data.sba.gov/dataset/ppp-foia
[9] Provided by CSBS in email dated February 28, 2022
[10] Detailed procedures for data preprocessing are provided in Appendix.
[11] Available on https://www.uscourts.gov/report-name/bankruptcy-filings

3) Other Control Variables

We also used county-level Gross Domestic Product data provided by the United States Bureau of Economic Analysis[12], population by county provided by the United States Census[13], the number of businesses by county in County Business Patterns provided by the United States Census[14], unemployment rate provided by the United States Bureau of Labor Statistics[15], and the number of Covid-19 cases provided by O. Wahltinez and others[16].

III. Exploratory Data Analysis

1) Distribution of PPP Loans

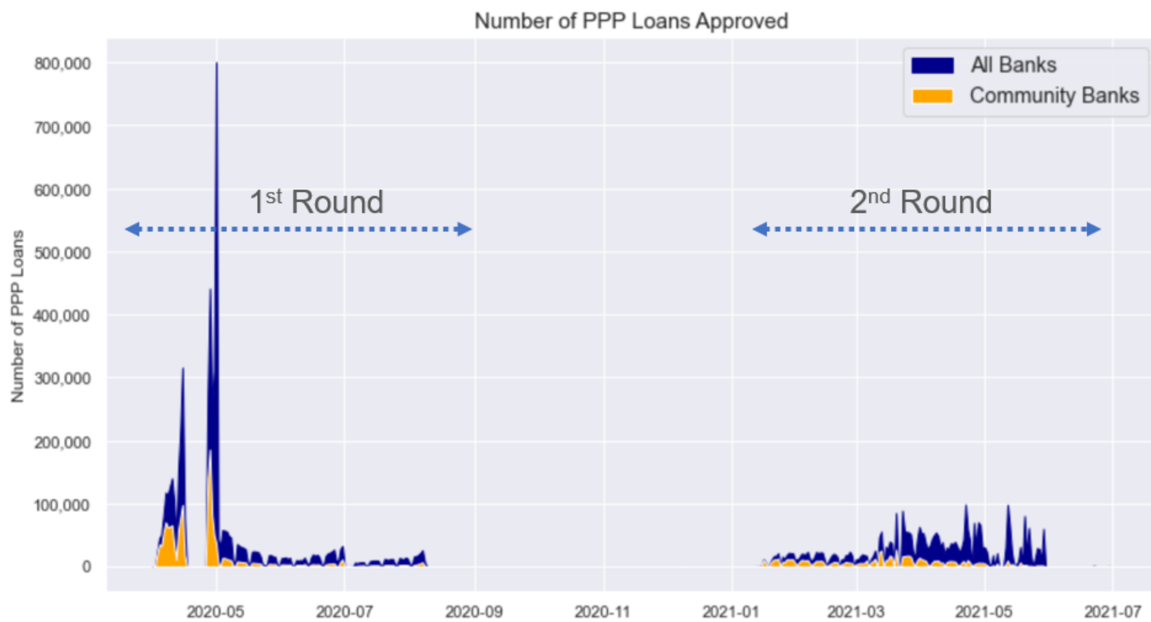

Figure 1: Number of First Draw PPP Loans Approved (4/1/20 - 6/30/21)

Our research only focuses on the First Draw PPP loan. The first approval date of the first draw was April 3rd, 2020. In Figure 1, We can see a remarkable spike starting from April with a peak on the 1st of May, the number of PPP loan approvals reaching 800,459 and the approved amount reaching 53 billion dollars. We can also notice that community bank-originated PPP loans account for a considerable portion; during April 2020, the average proportion of community bank PPP loans was 39.4%.

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12 Available on https://www.bea.gov/data/gdp/gdp-county-metro-and-other-areas
13 Available on https://www.census.gov/programs-surveys/popest.html
14 Available on https://www.census.gov/data/datasets/2019/econ/cbp/2019-cbp.html
15 Available on https://www.bls.gov/lau/#data
16 O. Wahltinez and others. 2020. "COVID-19 Open-Data: curating a fine-grained, global-scale data repository for SARS-CoV-2." Available on https://goo.gle/covid-19-open-data

	PPP First Draw Loans with Date Approved in first two months	PPP First Draw Loans in Entire PPP Period	Share of PPP First Loans with Date Approved in first two months
Total Number of PPP Loans	4,404,126	8,614,374	51.13%
Total Initial Approval Amount of PPP Loans	$504 billion	$589 billion	85.60%

Table 1. Number and Share of PPP First Draw Loans with Date Approved in First Two Months

Around 51% of PPP Loans were approved in the first two months of the entire PPP period, accounting for 85% of the total approval amount.

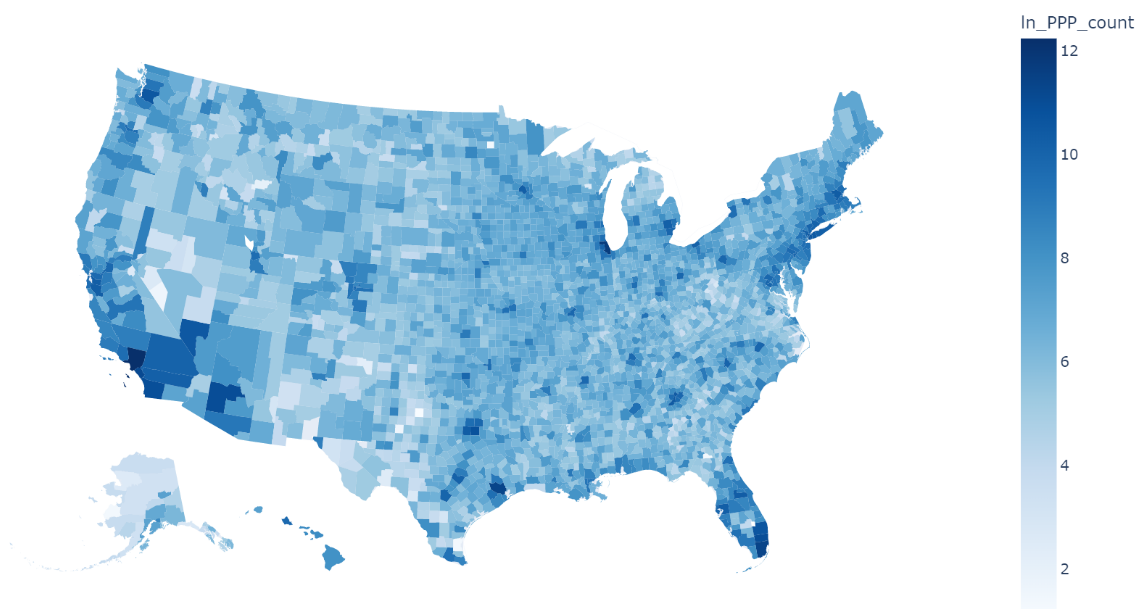

Figure 2: Number of PPP Loans Approved across Counties
(Natural Logarithmic Scale)

Figure 2 visualizes the geographical distribution of PPP loans across US counties, based on the borrower's address. The darker the color, the more loans are distributed in that county where the businesses are found. The scale is calculated in natural logarithm; the largest log value is 12.25 in Los Angeles county in California, reflecting 208,087 PPP loans approved in that county.

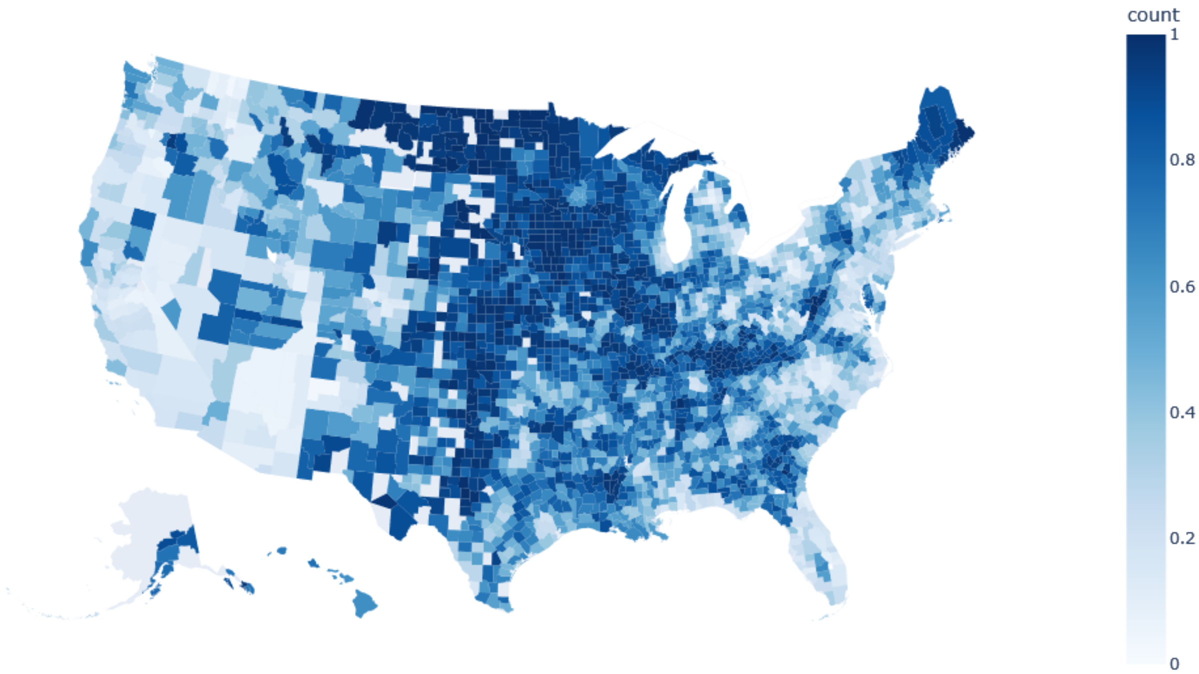

Figure 3: Share of PPP Loans offered by Community Banks across Counties

Figure 3 shows the share of the number of PPP loans originated by community banks by county. According to the map, community banks offered more PPP loans to businesses in counties in the middle United States. On the other hand, the share of PPP loans originated by community banks tends to be small in huge cities such as New York (12%) or Los Angeles (17%). The share of the amount of PPP loans offered by community banks shows a similar trend, which is mentioned in Appendix.

Regarding the industry distribution of businesses that received PPP loans, we look at the first two digits of the North American Industry Classification System (NAICS) code which refers to the 'industry sector'. Out of 25 industry sectors, '81 Other Services (except Public Administration)' ranked first (14.5%), followed by '54 Professional, Scientific, and Technical Services' (11.1%), and '23 Construction' (9.08%).

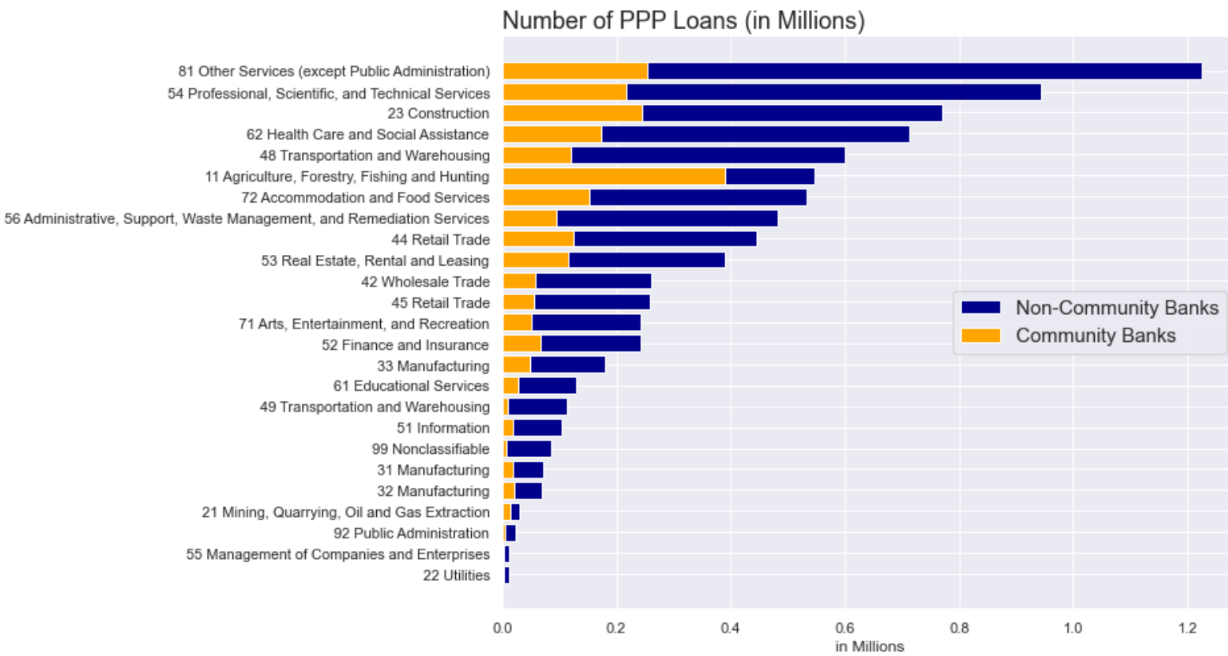

Figure 4: Number of PPP Loans distributed across Industry Sectors

Figure 4 represents the number of loans (in millions) allocated to each industry sector and the proportions of community and non-community bank-originated PPP loans in each industry sector. The industry sector with the highest proportion of community bank-originated PPP loans is the ‘11 Agriculture, Forestry, Fishing and Hunting’ sector, with the proportion reaching 71.2%.

2) Bankruptcy

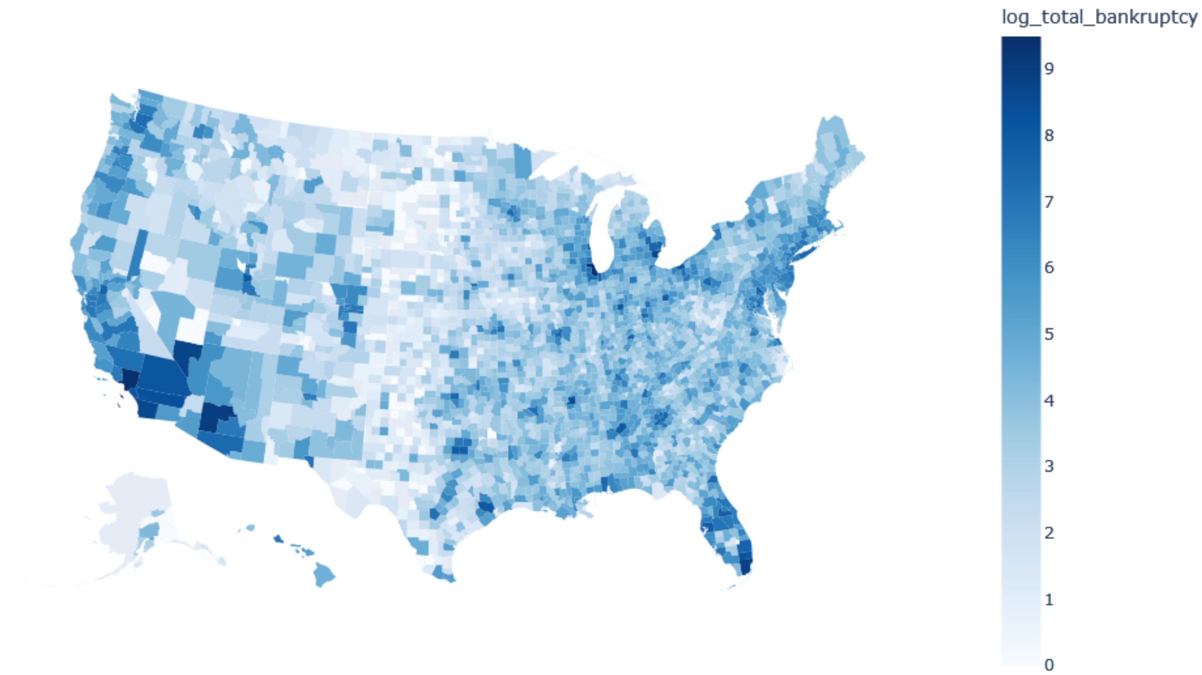

Figure 5: Number of Total (Business and Non-business) Bankruptcies across Counties (Natural Logarithmic Scale)

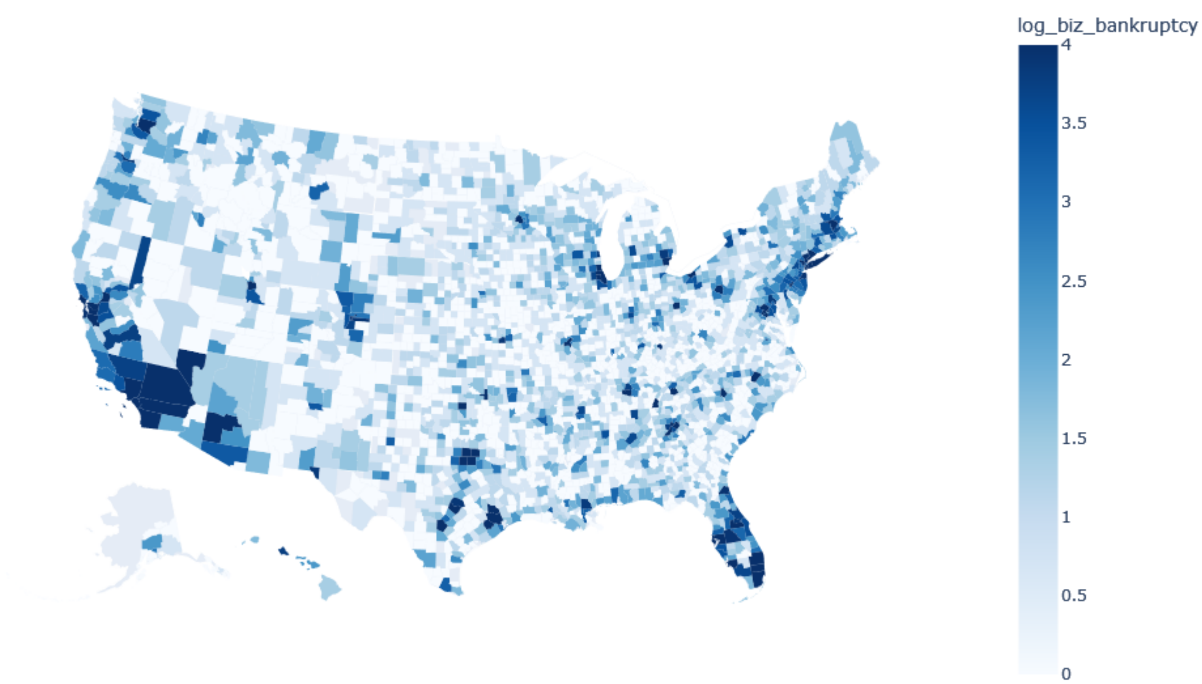

Figure 6: Number of Business Bankruptcies across Counties (Natural Logarithmic Scale)

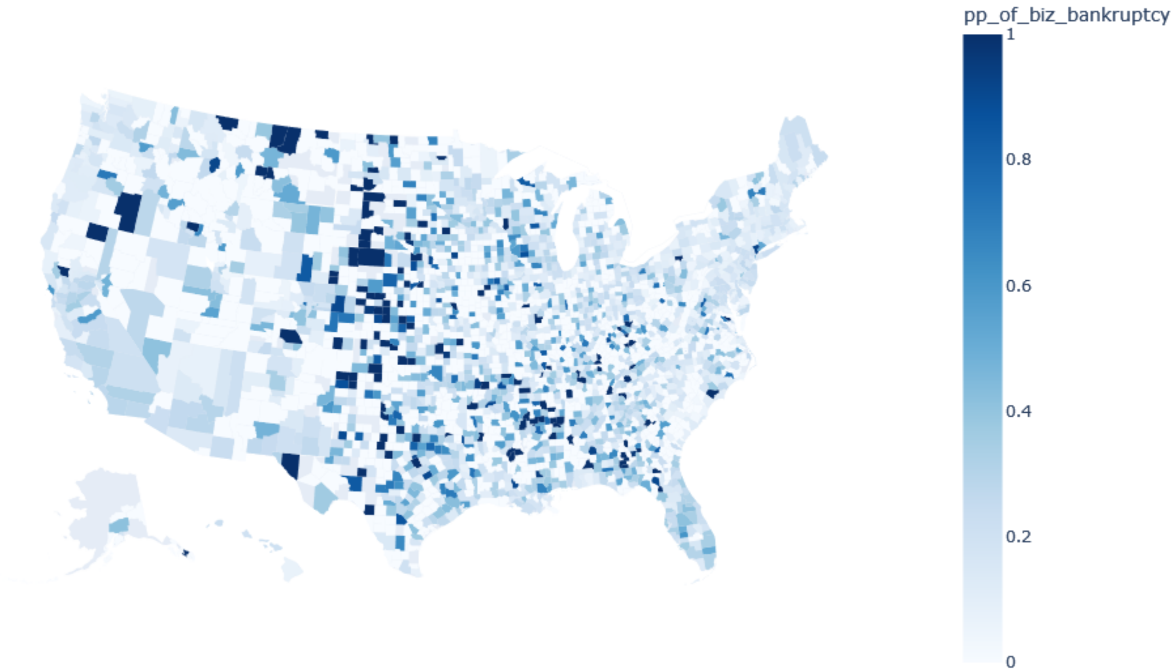

Figure 7: Percentage of Business Bankruptcy across Counties

Total bankruptcy consists of business and non-business bankruptcy, and the trends of total bankruptcy and business bankruptcy are similar, as shown in Figure 5 and Figure 6. The number of total and business bankruptcy is higher in urban areas (such as New York, Los Angeles) than rural areas (such as central U.S.).

On the other hand, the percentage of bankrupt businesses shows the opposite pattern. Figure 7 visualizes the percentage of businesses bankrupted by counties. In counties in the central U.S., the percentage is higher than in other areas, while the percentages are not high in urban counties. This suggests that rural regions are more likely to be impacted by the Covid-19 pandemic. As we see in Figure 3, the proportions of community bank-originated PPP loans are higher in the central U.S. regions. It suggests an overlap with the counties having a higher percentage of business bankruptcies.

IV. Statistical Analysis

In this research, we are interested in the association between the level of bankruptcy per county and the percentage of PPP loans originated by a CB lent to the borrowers in that county.

Using the geographical information in the PPP loan dataset, we computed the share of PPP loans originated by community banks in two different ways: the share of the number of loans, and the share of the approval amount of loans. We used these two metrics as indicators of community bank involvement in the county.

To account for each county, we used the county-level bankruptcy filings data from the U.S. Bankruptcy Courts. Since the data is updated and reported on a quarterly basis for the last 12-month period, during the period of PPP loan we have four relevant bankruptcy reports ranging (1) from April 1, 2020 to March 31, 2021, (2) from July 01, 2020 to June 30, 2021, (3) from September 1, 2020 to August 31, 2021, and (4) from January 1, 2021 to December 31, 2021. We used two bankruptcy measurements: total bankruptcy (business and non-business bankruptcy), and business bankruptcy.

<table>
<tr><td>Period Number</td><td>0</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td><td>7</td></tr>
<tr><td>Time Period</td><td>Jan 01, 2020 - Mar 31,, 2020</td><td>Apr 01, 2020 - Jun 30, 2020</td><td>July 01, 2020 - Sep 31, 2020</td><td>Oct 01, 2020 - Dec 31, 2020</td><td>Jan 01 2021 - Mar 31, 2021</td><td>Apr 01, 2021 - Jun 30, 2021</td><td>July 01, 2021 - Sep 30, 2021</td><td>Oct 01, 2021 - Dec 31, 2021</td></tr>
<tr><td>Bankruptcy Period 1</td><td></td><td colspan="4">Bankruptcy in Period 1-4 (1)</td><td></td><td></td><td></td></tr>
<tr><td>Bankruptcy Period 2</td><td></td><td></td><td colspan="4">Bankruptcy in Period 2-5 (2)</td><td></td><td></td></tr>
<tr><td>Bankruptcy Period 3</td><td></td><td></td><td></td><td colspan="4">Bankruptcy in Period 3-6 (3)</td><td></td></tr>
<tr><td>Bankruptcy Period 4</td><td></td><td></td><td></td><td></td><td colspan="4">Bankruptcy in Period 4-7 (4)</td></tr>
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Table 2: Periods Used in Bankruptcy Data

To match the periods of bankruptcy filings report, we aggregated the PPP loans[17] and Covid-19 cases[18] into seven quarters that correspond to the bankruptcy reporting periods, shown in Table 3.

Period Number	0	1	2	3	4	5	6	7
Time Period	Jan 01, 2020 - Mar 31, 2020	Apr 01, 2020 - Jun 30, 2020	July 01, 2020 - Sep 31, 2020	Oct 01, 2020 - Dec 31, 2020	Jan 01 2021 - Mar 31, 2021	Apr 01, 2021 - Jun 30, 2021	July 01, 2021 - Sep 30, 2021	Oct 01, 2021 - Dec 31, 2021
(Based on Date Approved) The percentage of the number/amount of loans originated by community banks in county *i* and period j	NA (PPP not yet started)	CB_percentage1	CB_percentage2	CB_percentage3	CB_percentage4	CB_percentage5	NA (PPP ended)	
Covid-19 cases for county i and period j	CovidCases0	CovidCases1	CovidCases2	CovidCases3	CovidCases4	CovidCases5	CovidCases6	CovidCases7

Table 3: Variables of Interest Created Corresponding to the Bankruptcy Reporting Periods

1) Model specification

To explore the effect of one period's PPP loan on different periods of bankruptcy, we fix the period of PPP loans based on the approval date and move the bankruptcy window in different regressions; we call this rolling window regression.

We run the following rolling window regression model for each of the four bankruptcy periods. And in each period, we use one of the two different outcome variables (total bankruptcy or business bankruptcy), and one of the two different variables of interest. Hence, we have a total of 16 regression models (= 2 x 2 x 4 models).

[17] PPP loan period (Date Approved): April 3, 2020 - June 29, 2021
[18] Covid cases: first case recorded on January 20, 2020

$$Y_i = \alpha + \beta_1 CBPercentage_i + \beta_2 Population_i + \beta_3 GDP_i + \beta_4 NumBiz_i + \sum_t \gamma_t CovidCases_{it} + e_i$$

Y_i	the outcome variable, the number of total bankruptcy / business bankruptcy in county *i.* The data in four different periods are used.
$CBPercentage_i$	the variable of interest, the percentage of the number/amount of loans originated by community banks in county *i* (two different variables of interest)
$Population_i$	population in county *i* as of April 1, 2020
GDP_i	GDP in county *i* in 2020
$NumBiz_i$	the number of businesses in county *i* in 2019
$CovidCases_{it}$	the number of Covid-19 cases in county *i* in period *t*

Table 4: Variables used in the regression model

For each period, we ran a regression using the model above, and Table 4 shows the description of variables used in the model. Separately, we also ran the regression models with state-fixed effects to eliminate the risk of endogeneity rising from the differences in state policies (i.e. Covid-19 policies) which may affect the economy and bankruptcy.

2) Summary of Results

	Bankruptcy in Period 1-4 (1)	Bankruptcy in Period 2-5 (2)	Bankruptcy in Period 3-6 (3)	Bankruptcy in Period 4-7 (4)
Percentage of loan by CB				
the number of loans in Periods 1-4	- 59.1809*** (14.676)			
the number of loans in Periods 1-5		-12.0121 (13.796)	- 3.3380 (13.061)	0.3975 (12.356)
the amount of loans in Periods 1-4	- 57.4220*** (14.303)			
the amount of loans in Periods 1-5		-19.7291 (13.433)	-11.4549 (12.7)	-7.5245 (12.037)
N	2984	2976	2971	2952

Notes: This table reports the estimated coefficients. Each column reports the regression coefficient estimates for different periods from Table 3. Standard errors are reported in parentheses. Statistically significant coefficient estimates are presented with *** (significance level α=0.01).

Table 4: Regressions without State-Fixed Effects,
Outcome Variable: Total Bankruptcy

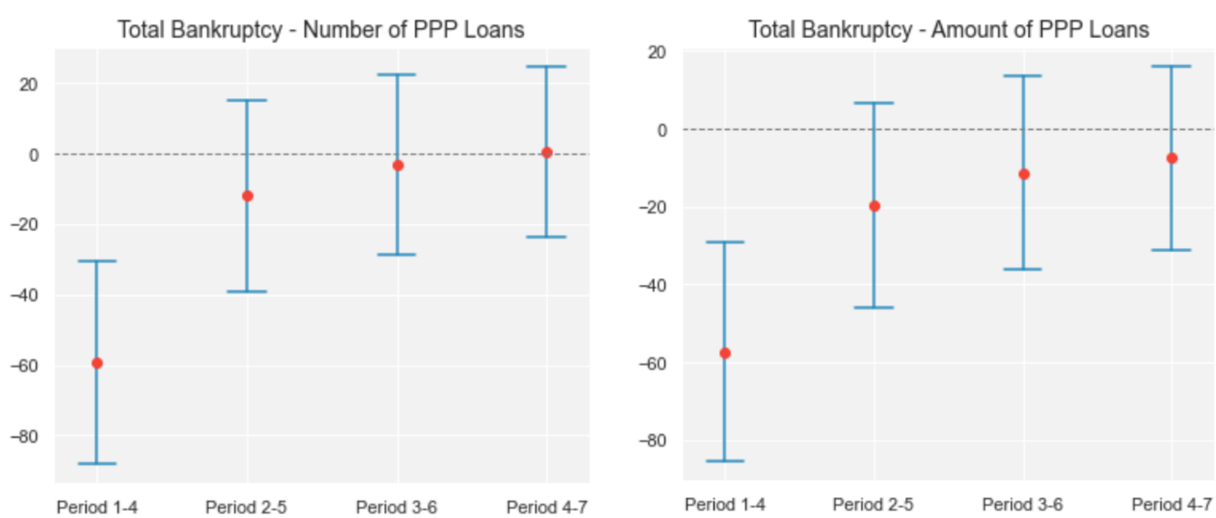


Figure 8: Confidence Intervals of Coefficient Estimates from Table 4

The results of the regressions are shown in Tables 4, 5, and Figures 8, 9. On average, it is observed that a county with a 1% higher PPP loan (in terms of approval amount) originated by a community bank is associated with about 7 to 57 fewer total bankruptcy filings across all the PPP loan approval periods (April 3, 2020 - June 29, 2021). The coefficient in the first period is statistically significant at a significance level of α=0.01.

Since most PPP loans were approved in May 2020, the association between total bankruptcy and PPP loans is strongest and statistically significant in the first period of the regression. As we progress in time and move the window, especially into the period after the PPP ends, the association between bankruptcy and PPP loans diminishes.

	Bankruptcy in Period 1-4 (1)	Bankruptcy in Period 2-5 (2)	Bankruptcy in Period 3-6 (3)	Bankruptcy in Period 4-7 (4)
Percentage of loan by CB				
the number of loans in Periods 1-4	0.7049 (0.834)			
the number of loans in Periods 1-5		1.2044 (0.715)	2.1283*** (0.581)	1.8532*** (0.429)
the amount of loans in Periods 1-4	0.7516 (0.813)			
the amount of loans in Periods 1-5		1.0908 (0.696)	1.9364*** (0.565)	1.7720*** (0.418)
N	2984	2976	2971	2952

Notes: This table reports the estimated coefficients. Each column reports the regression coefficient estimates for different periods from Table 3. Standard errors are reported in parentheses. Statistically significant coefficient estimates are presented with *** (significance level α=0.01).

Table 5: Regressions without State-Fixed Effects,
Outcome Variable: Total Business Bankruptcy

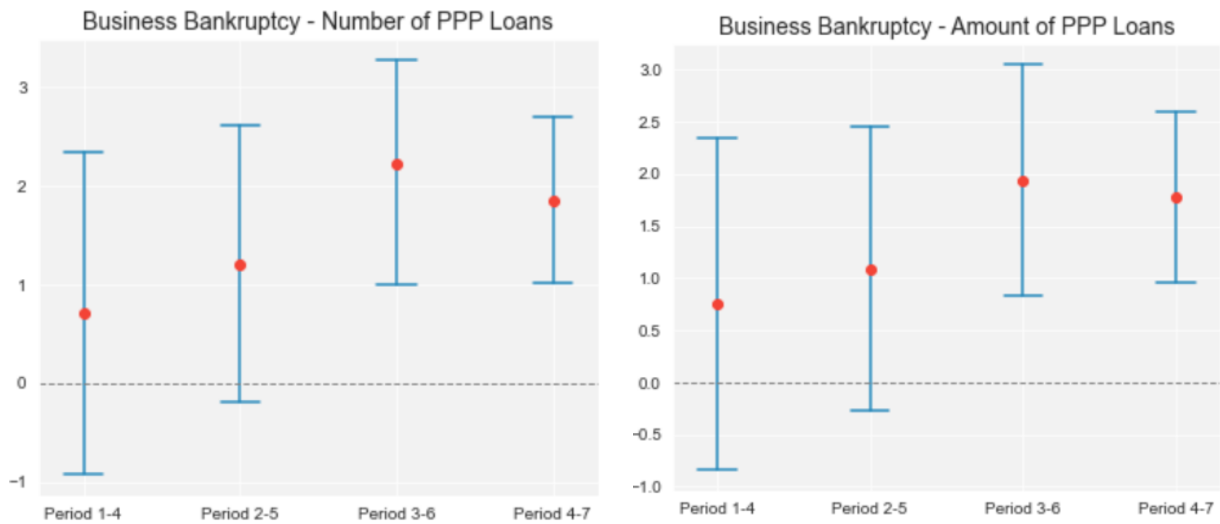


Figure 9: Confidence Intervals of Coefficient Estimates from Table 5

During the first two periods, the coefficients are positive but not statistically significant, while in the last two periods there are positive but statistically significant associations between a higher percentage of PPP loans originated by community banks and bankruptcy.

Since counties in which community banks played a greater role in providing PPP loans were affected more severely by Covid-19, the number of business bankruptcies were likely to be prominent in these counties in post-PPP periods. Moreover, the large number of PPP loans offered in previous periods (e.g., six months ago) is not strongly associated with reducing business bankruptcy. In turn, this suggests the possibility that PPP loans may only have short-term effects on the financial soundness of businesses.

	Bankruptcy in Period 1-4 (1)	Bankruptcy in Period 2-5 (2)	Bankruptcy in Period 3-6 (3)	Bankruptcy in Period 4-7 (4)
Percentage of loan by CB				
the number of loans in Periods 1-4	- 50.3868** (18.123)			
the number of loans in Periods 1-5		6.8664 (16.807)	16.8955 (16.028)	14.6335 (15.037)
the amount of loans in Periods 1-4	- 34.8371** (17.241)			
the amount of loans in Periods 1-5		3.4273 (15.973)	10.3059 (15.110)	9.1654 (14.210)
N	2984	2976	2971	2952

Notes: This table reports the estimated coefficients. Each column reports the regression coefficient estimates for different periods from Table 3. Standard errors are reported in parentheses. Statistically significant coefficient estimates are presented with ** (significance level α=0.05).

Table 6: Regressions with State-Fixed Effects,
Outcome Variable: Total Bankruptcy

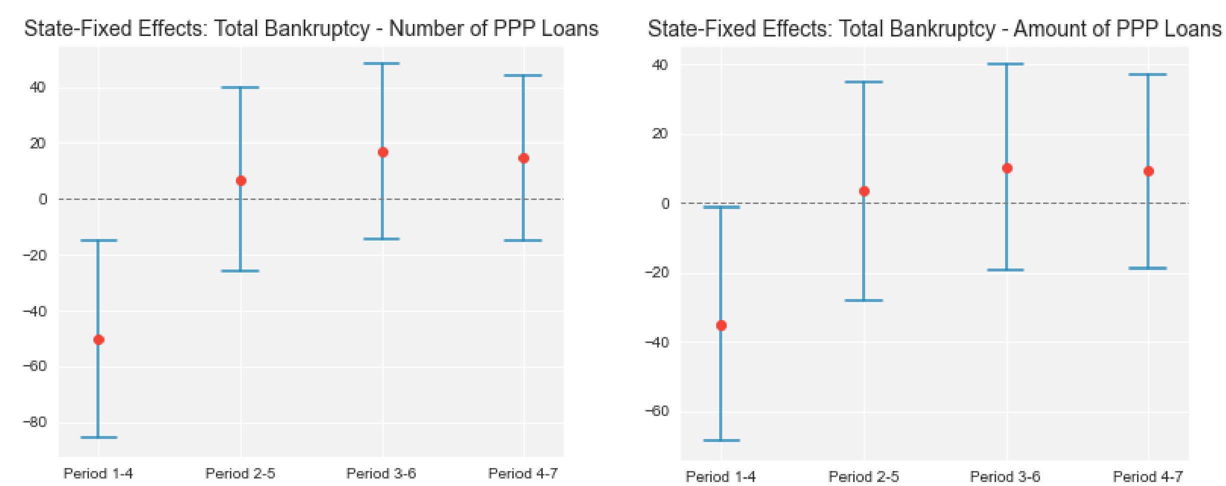
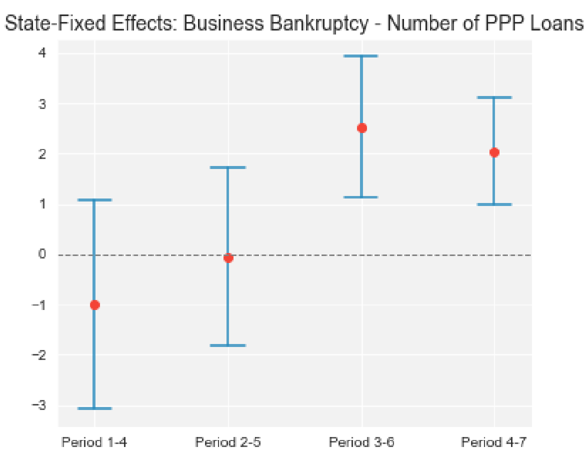


Figure 10: Confidence Intervals of Coefficient Estimates from Table 6

	Bankruptcy in Period 1-4 (1)	Bankruptcy in Period 2-5 (2)	Bankruptcy in Period 3-6 (3)	Bankruptcy in Period 4-7 (4)
Percentage of loan by CB				
the number of loans in Periods 1-4	- 1.0098 (1.057)			
the number of loans in Periods 1-5		- 0.052 (0.903)	2.5289*** (0.712)	2.0478*** (0.539)
the amount of loans in Periods 1-4	- 0.3890 (1.005)			
the amount of loans in Periods 1-5		0.2277 (0.858)	2.0399*** (0.672)	1.7843*** (0.510)
N	2984	2976	2971	2952

Notes: This table reports the estimated coefficients. Each column reports the regression coefficient estimates for different periods from Table 3. Standard errors are reported in parentheses. Statistically significant coefficient estimates are presented with *** (significance level α=0.01).

Table 7: Regressions with State-Fixed Effects,
Outcome Variable: Total Business Bankruptcy



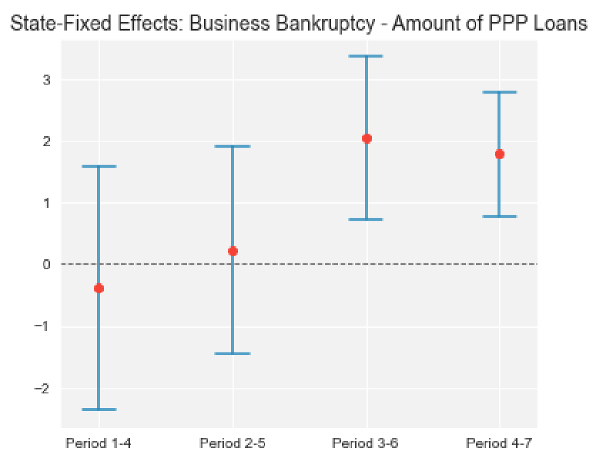


Figure 11: Confidence Intervals of Coefficient Estimates from Table 7

Table 6 and 7 show the regression models with state-fixed effects.

For the bankruptcy period 1-4, the regression model with state-fixed effects in Table 6 and the model without state-fixed effects in Table 4 exhibit a similar pattern in terms of direction and statistical significance of the coefficient estimates.

3) Interpretations

a) CB-originated PPP loans help local community

The results of the regression models show that a larger share of PPP loans originated by community banks is associated with a smaller number of total (business and non-business) bankruptcy in April 2020 - March 2021. It can be attributed to the fact that the majority of the PPP loan proceeds went to payroll proceeds; for 5,252,366 (about 88.5%) PPP loans, 90% of the loan amount was allocated for payroll costs. This suggests that employees in small businesses benefited more from the PPP loans as they received a greater amount of PPP loan proceeds. Thus, the community banks may have potentially contributed to lowering total bankruptcy through these PPP loans.

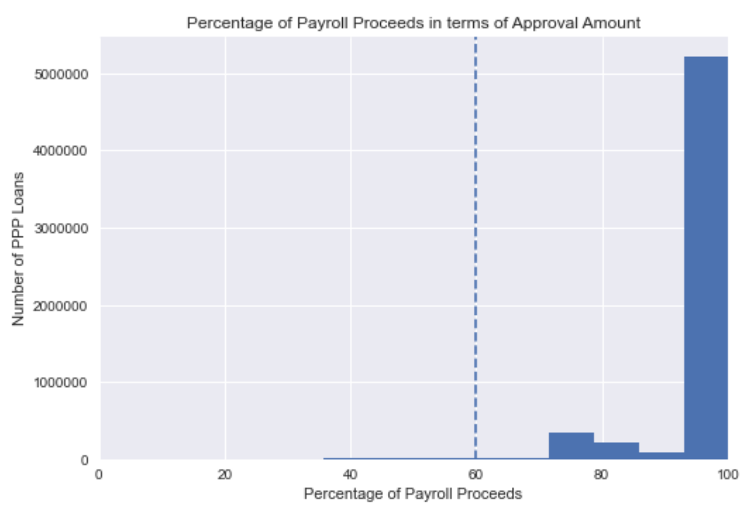


Figure 12: Percentage of Payroll Proceeds in terms of Approval Amount

b) PPP's nature may have limited CB's role in reducing business bankruptcy

Nonetheless, the results do not suggest a negative correlation between the share of community banks in PPP loans and business bankruptcy. One of the possible reasons is that PPP loans might not have improved the financial stability of businesses.

Even though small businesses also had to pay their rent, mortgage interests, fixed costs, and operating costs throughout the Covid-19 pandemic, most of PPP loans went to payroll costs. As a result, PPP loans might not have injected adequate liquidity into small businesses under severe conditions.

Since businesses were encouraged to spend at least 60% of the proceeds on payroll costs to be eligible for PPP loans forgiveness[19], this rule may have affected the usage of PPP loans and weakened the association between the share of CB-originated PPP loans and business bankruptcy.

c) Diminishing Association between PPP Loans and Total Bankruptcy Over Time

From the regression results, the magnitude of the coefficient estimates for bankruptcy diminish over time, from 19.73 in period 2 to 11.45 in period 3 and to 7.52 in period 4 (Table 4).

One possible reason is the gap between Round 1 and Round 2 of First Draw PPP; as shown in Figure 13, the application for PPP loans stopped between August 9, 2020 and January 14, 2021. However, the daily new Covid-19 cases surged from about 50,000 in August 2020 to a maximum of about 300,0000 in January 2021. The local economy and small businesses were likely to be hit the hardest during this surge in Covid-19 cases.

[19] U.S. Small Business Administration. "PPP loan forgiveness." Accessed on April 24, 2022. https://www.sba.gov/funding-programs/loans/covid-19-relief-options/paycheck-protection-program/ppp-loan-forgiveness

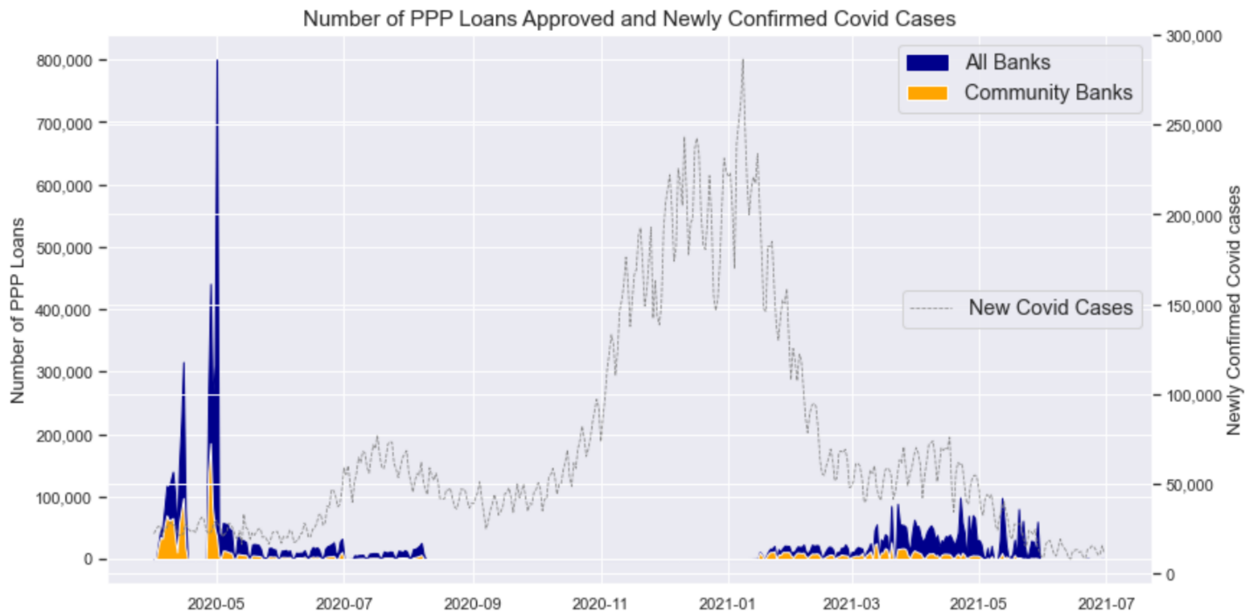


Figure 13: Number of PPP Loans Approved and Newly Confirmed Covid Cases (4/1/20 - 6/30/21)

Another possible reason is that since over 50% of the PPP first draw loans were approved before June 1, 2020 (and accounts for about 85% of the total approved amount, see Table 1), there were fewer PPP loans approved in the later periods of 2021, hence the coefficient estimates decreased.

V. Conclusion

1) Summary

PPP and Community Banks

Studies have suggested that capital-rich large companies weather the storm better than small businesses in times of economic crisis. According to a JP Morgan Chase Institute[20] research in 2016 covering transactional data from 597,000 small businesses, half of the SMEs operate with less than 27 days of cash reserve.

[20] JP Morgan Chase & Co. Institute. “Cash is King: Flows, Balances, and Buffer Days.” September 2016. https://www.jpmorganchase.com/institute/research/small-business/report-cash-flows-balances-and-buffer-days.htm

The Covid-19 pandemic crisis is no different in terms of damage to the economy. This is why, on top of the Federal Reserve's injection of money into the wide financial system, the SBA has devised another financial policy, PPP, that specifically targets small businesses. The economy cannot be healthy without a vibrant community of diverse small businesses, and it is also critical to support entrepreneurship. Given their unique characteristics, community banks are therefore hypothesized. We have shown evidence above to support this report to be in a unique position to help small businesses.

Community Banks' Contribution to Making Small Businesses and Communities more resilient

With evidence from the PPP loan data and exploratory data analysis, community banks, in general, serve communities that are more prone to bankruptcy, especially those that are counties in the central U.S. In our statistical analysis, counties with more PPP loans originated by community banks (in terms of approval amount) are associated with a lower level of cases of bankruptcy filings (business and non-business) during the Covid-19 pandemic, and it is consistent across all the time periods.

Our regression results show a statistically significant negative association between the percentage of CB-originated PPP loans and the total bankruptcy cases (business and non-business). These results also suggest that community banks contributed to achieving the policy goal of PPP as intended in helping the recipients of payroll in local communities.

The association between the percentage of CB-originated PPP loans and the total business-only bankruptcies is not statistically significant and further analysis would be necessary for understanding the causality between PPP loans and bankruptcies.

Unlike the PPP loans that are specifically designed to maintain employment, other less payroll-focused policies were introduced by the SBA, such as the Restaurant Revitalization Fund (RRF), COVID-19 Economic Injury Disaster Loan (EIDL), and Shuttered Venues Grant[21]. These economic stimulus policies may be more effective in

[21] U.S. Small Business Administration. "COVID-19 relief options." Accessed on April 24, 2022. https://www.sba.gov/funding-programs/loans/covid-19-relief-options

reducing business bankruptcies.

Our regression results also suggest that the association between total bankruptcy and CB-originated PPP loans mainly offered in Round 1 diminishes over time. This gap, along with the surge in Covid-19 cases during this gap, may have made businesses more vulnerable as PPP loans were not available. Timely interventions against external shocks such as Covid-19 will be critical in mitigating the adverse economic consequences.

Looking Ahead

The evidence from our research has solidified that community banks do play important financial intermediary roles during economic shocks. When the next financial crisis occurs, community banks can be expected to play the important role of providing liquidity to small businesses, providing their employees and families with a much-needed financial cushion that may be harder to access through other traditional financial channels.

2) Limitations of Analysis

Our analysis may be subject to the following limitations mainly due to the availability of relevant data:

Firstly, the characteristics (such as the number of employees, industry sector, size) of the businesses that did not apply for or did not get approval for PPP loans, and those that got the loan from CBs and non-CBs are unknown. These characteristics also affect the probability of businesses going bankrupt and may cause endogeneity issues.

Secondly, monthly or quarterly bankruptcy data is unavailable, and thus we were unable to analyze the immediate impacts of PPP loans on bankruptcies. As we suggested, based on the regression analysis results, the impacts of PPP may diminish over time. However, we were not able to analyze the prolonged effects in detail.

Lastly, data on policies other than PPP, which may also affect the bankruptcy, are not included in our models as control variables.

VI. Appendix

1. Data Pre-processing

a) Handling missing values in PPP data

In the combined PPP data, there are certain columns with a large number of missing values. Specifically:

- Features with a high percentage of null values:

  For features below with more than 90% null values, these features are not included in our analysis:

  > "FranchiseName", "UTILITIES_PROCEED",
  > "MORTGAGE_INTEREST_PROCEED", "RENT_PROCEED",
  > "REFINANCE_EIDL_PROCEED", "HEALTH_CARE_PROCEED",
  > "DEBT_INTEREST_PROCEED", "NonProfit"

- Features of high percentage of unanswered values:

  There are high "Unanswered" ratio in the values in feature "Race":

Unanswered	8,693,435
White	1,562,677
Black or African American	819,789
Asian	298,075
American Indian or Alaska Native	84,700
Native Hawaiian or Other Pacific Islander	10,383
Puerto Rican	667
Multi Group	54
Eskimo & Aleut	21

- Furthermore, a high ratio of "Unknown/NotStated" values in the feature "Ethnicity":

Unknown/NotStated	8,197,445
Not Hispanic or Latino	2,908,127
Hispanic or Latino	364,229

Hence, the features “Race” and “Ethnicity” are also deemed of questionable value and are not used in the analysis.

b) Converting PPP location data into County (FIPS) information

In order to incorporate county-level bankruptcy data into our analysis, we had to retrieve county information from the borrower’s address which is not included in the SBA’s original PPP loan dataset.

We took advantage of the Python library called ‘uszipcode’[22], which is a powerful zip code search engine that retrieves relevant geographic information from a zip code database. Using this library, we obtained the state and county information from the borrower’s zip code. After this, we used county-FIPS mapping to obtain the corresponding county FIPS code. Then, we merged the bankruptcy dataset with the PPP loan dataset using the FIPS code to be used for our regression analysis.

[22] https://uszipcode.readthedocs.io/index.html

2. Additional Exploratory Data Analysis

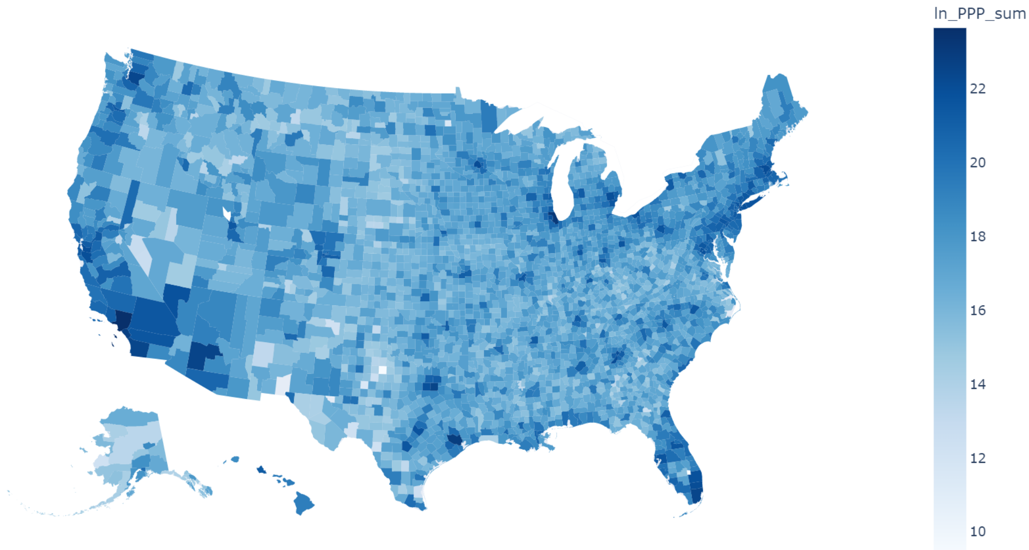


Figure 14: Amount of PPP Loans distributed across Counties

Figure 14 visualizes the geographical distribution of PPP loan amounts across U.S. counties, based on the borrower's address. The darker the color, the larger amount of PPP loans distributed in that county where the businesses are based. The scale is calculated in natural log; the largest log value is 23.65 in Los Angeles county in California, which reflects about 18.7 billion dollars of PPP loans approved in that county.

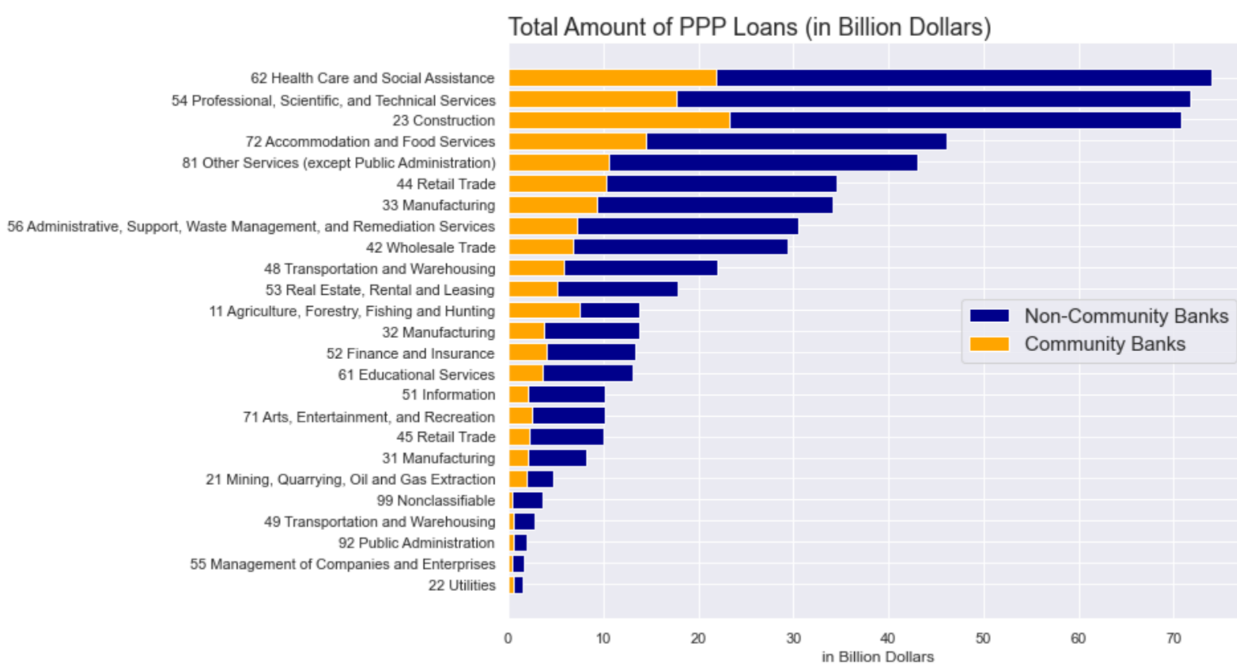


Figure 15: Amount of PPP loans distributed across industry sectors

Figure 15 represents the dollar amount of loans (in billions) distributed to each industry sector and the proportions of community and non-community bank-originated PPP loans in each industry sector. We can notice that the dollar amount rank does not exactly coincide with the rank for the number of loans; whereas ‘81 Other Services (except Public Administration)’ sector ranked first in terms of the number of PPP loans, in terms of dollar amount, ‘62 Health Care and Social Assistance’ sector ranked first.

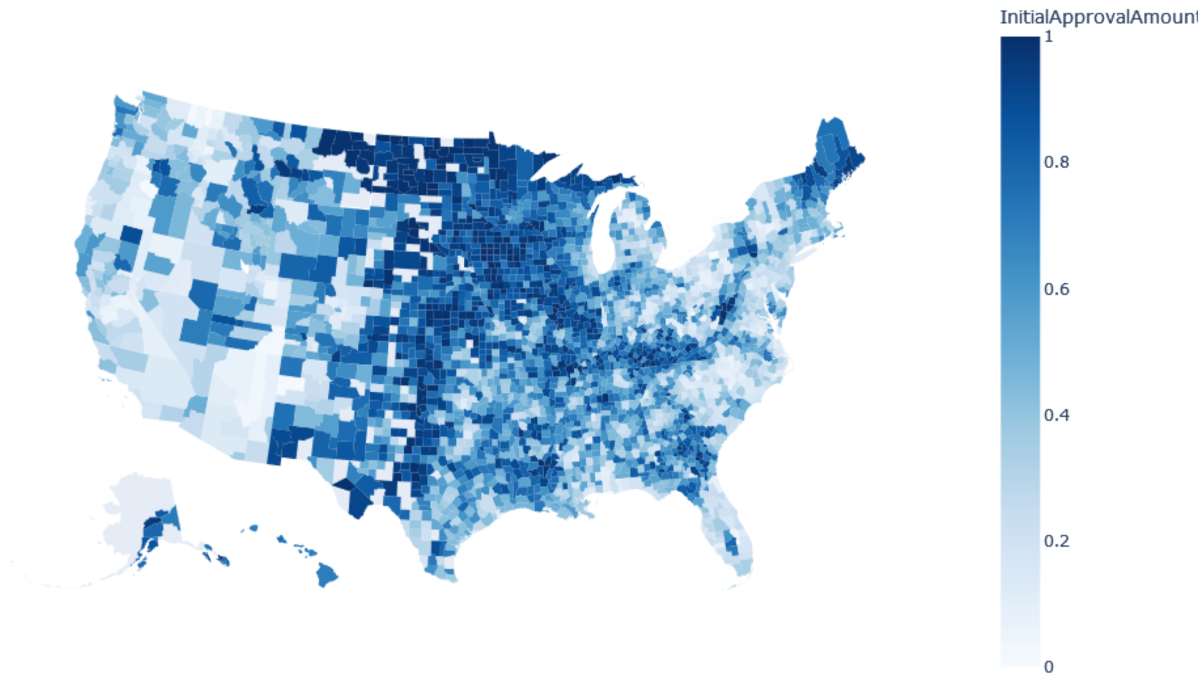


Figure 16: Share of PPP Loan Amount offered by Community Banks across Counties

Figure 16 shows the share of the amount of PPP loans originated by community banks by county. According to the map, community banks offered more PPP loans to businesses in counties in the central United States. On the other hand, the share of PPP loans originated by community banks tends to be small in major cities such as New York (12%) or Los Angeles (15%). It shows a similar pattern with Figure 3.

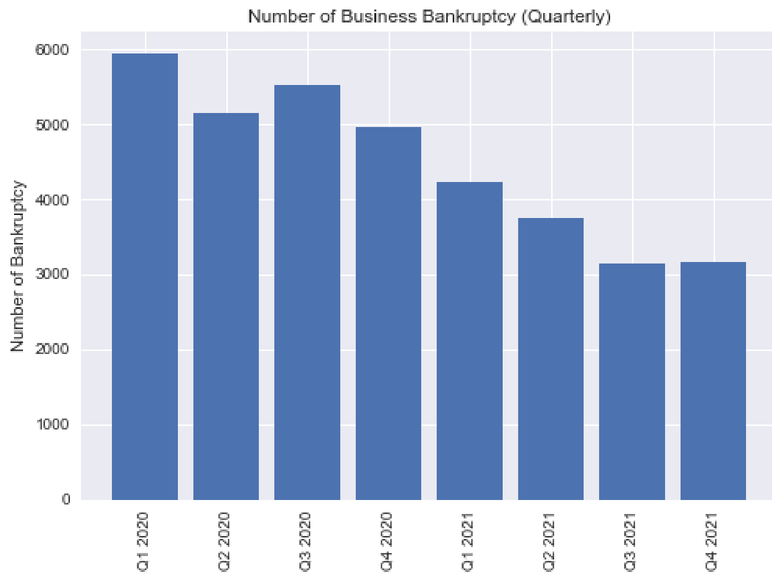


Figure 17: Number of Business Bankruptcies in each Quarter (2020-2021)

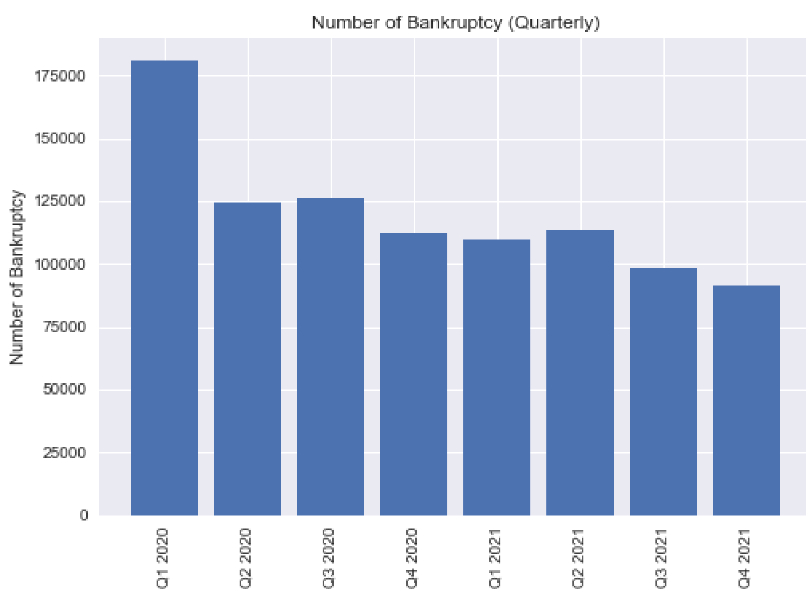


Figure 18: Number of Total Bankruptcies in each Quarter (2020-2021)

Figure 17 and 18 both show a downward trend in bankruptcy filings over time.

VII. References

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