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Paycheck Protection Program: County-Level Determinants and Effect on Unemployment

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Paycheck Protection Program: County-Level Determinants and Effect on Unemployment*

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Abstract

This paper uses U.S. county-level data to study the determinants and effects of the Paycheck Protection Program (PPP). The paper first overviews the timeline and institutional aspects of the PPP, implemented in the second quarter of 2020 and worth about $669 billion in forgivable small business loans guaranteed by the Small Business Administration (SBA). It then studies the determinants of the county-level ratios of PPP loans per job lost during the original unemployment surge associated with the onset of the COVID-19 pandemic in late March 2020 and finds that it does not appear to be a major driver of the PPP loan concentration; instead, it was primarily driven by the local banking conditions and demographic factors. The second part of this paper uses the method of local projections to determine whether the participation in the PPP program improved economic conditions following its implementation. Impulse responses in the standard linear framework are positive and statistically significant, albeit economically negligible, suggesting that the PPP was entirely ineffective in stabilizing labor market conditions. Extending the framework to state-dependent local projections reverses this result: PPP lending had a significant effect on reducing unemployment on average and especially in counties with strong banking liquidity and an educated labor force.

Keywords: COVID-19 pandemic, Paycheck Protection Program, local projections, unemployment rate

JEL Codes: G21, G28

* The views presented in this paper are the author's and do not reflect the official position of the Federal Reserve Bank of Dallas or the Federal Reserve System. I would like to thank Scott Frame for his comments on an earlier draft. This version of the paper is preliminary; comments are welcome.

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1 Introduction

The COVID-19 pandemic and the subsequent policy and private sector responses to it came at the cost of an unprecedented havoc in the United States labor market in the spring of 2020. Initial claims for unemployment insurance of about 3.3 million were filed during the week ending on March 21, 2020, surpassing the previous weekly report almost 12-fold. The following week the number of these claims doubled and proceeded to stay above the 3 million mark into May.[1] The need to for immediate unemployment relief was quickly understood by the U.S. lawmakers and on March 27, 2020, the Coronavirus Aid, Relief, and Economic Security Act (the CARES Act) was signed into law. While forgivable loans to small businesses through the Paycheck Protection Program comprised only about 16% of the funding made available through the $2.2 trillion CARES Act, the Paycheck Protection Program and Health Care Enhancement (PPPHCE) Act, signed into law on April 24, 2020 increased the PPP funding to $669 billion. As Autor et al. (2020) remind, the program's size was roughly two thirds of the entire American Recovery and Reinvestment Act of 2009, the primary fiscal tool to combat the Great Recession of 2008-2009, with the majority of funds being disbursed over a five-week period.

This paper studies two issues related to the PPP using various definitions of PPP funding per job lost during the initial hit of the COVID-19 Recession to the U.S. labor markets. First, did the program primarily target geographical areas that were the hardest hit by the surge in unemployment in the Spring of 2020? The answer appears to be 'no'. The simple correlations between the changes in the unemployment rate between March and April 2020 and different measures of PPP loans per job lost are consistently negative and adjusting for the county banking conditions and demographic characteristics makes them economically much larger and statistically significant. This is consistent with the recent work of Granja et al. (2020) who find that generally the PPP funds did not go to the hardest hit areas using state-level data.

Second, I study the effect of PPP funding per job lost on subsequent county-level labor market outcomes using the method of local projections. PPP's main objective was encouraging small businesses to maintain pre-crisis payroll levels following the initial surge, reflected in the April 2020 unemployment rate numbers, at least through September 2020, the targeted expiration date of the

[1] Forsythe et al. (2020) document that the job vacancies collapsed by over 40% over the subsequent month. While conventional wisdom points to the stay-at-home orders issued by state and local authorities across the United States, Baek et al. (2020) find that less than a quarter of the increase in the initial claims for unemployment insurance in March and April 2020 were explained by them, with the rest coming from other sources, such as voluntary mobility reduction, consumer and business pessimism, etc.

program. Much of the recent literature has focused on the program's firm-level effects, which is appropriate for gauging its direct impact. However, its likely secondary effects associated with the resulting higher level of local business activity can only be captured by broader measures. Furthermore, since the overwhelming majority of PPP funds were disbursed through banks, banking data should be highly informative as to the determinants of PPP concentrations and their subsequent effects. Counties with relatively large exposures to PPP loan balances should have experienced larger subsequent *declines* in unemployment, resulting from both the direct effects on participating firms and knock-on effects on other local businesses. Using the local projections approach, I construct impulse responses of unemployment rate changes relative to their April 2020 levels that mark the initial surge in the pandemic-related unemployment. A simple linear framework yields impulse responses that are positive and statistically significant, albeit economically small, suggesting that the program failed to reduce unemployment in areas with the highest levels of PPP funding per job lost. However, switching to state-dependent local projections that condition impulse responses on county-level demographic and banking controls reverses this result: PPP loan concentration reduces unemployment rates by large amounts, especially in larger counties with strong pre-pandemic banking liquidity positions and a relatively educated labor force. This finding implies that accounting for county-level heterogeneity should be a key feature of the empirical design evaluating the transmission of PPP funding to labor markets.

The rest of the paper is organized as follows. Section 2 presents the data used in this paper and details the construction of county-level banking variables, including several ratios of PPP loans per job lost. Section 3 provides a brief overview of the impact of the COVID-19 pandemic on labor markets across the U.S. and details the institutional aspects of the PPP implementation. Section 4 presents a model of determinants of PPP loans per job lost ratios at the county level. It finds that they were largely driven by the local banking and demographic conditions, rather than labor market outcomes. Section 5 uses a local projections framework to study the effect of PPP funding on subsequent county-level unemployment rates and finds that the PPP participation did improve local labor market conditions but modest amounts in a framework that allows for state-dependent heterogeneity. Section 6 offers concluding remarks.

2 Data

Data are assembled from different sources and have three broad categories. First, monthly county-level unemployment rates from the Bureau of Labor Statistics are available from January 1990 through September 2020. Since these data are not seasonally adjusted, seasonal adjustment is performed for county unemployment rates over January 1990 through March 2020 using the U.S. Census X-13 algorithm.[2] Unemployment rates starting in April 2020 are taken at reported values, since the pandemic effects completely overwhelmed the influence of seasonal factors. To provide a benchmark for analyzing their dynamics, I use the national unemployment rate from the FRED database maintained by the Federal Reserve Bank of St. Louis.

Second, the key variables of interest are related to the amount of PPP loans normalized by various measures of changes in employment or unemployment at the county level.[3] Collectively, they provide a comprehensive description of PPP lending per job lost during the initial pandemic-related surge in unemployment. The first set of empirical exercises in this paper estimates models of their potential determinants, the second set studies their effect on subsequent economic activity. The joint use of these four measures and the consistency of the estimated model results that rely on them lends a sense of robustness of this empirical framework. These measures are as follows:

- $PPP2dU = \frac{PPP}{\Delta U}$ is the ratio of the PPP loans normalized by the county-level March-to-April change in unemployment;
- $PPP2dE = -\frac{PPP}{\Delta E}$ is the ratio of the PPP loans normalized by the negative March-to-April change in county-level employment;
- $PPP2WdU = \frac{PPP}{W\Delta U}$ is the ratio of the PPP loans normalized by the county-level March-to-April change in unemployment multiplied by W, the share of small businesses employment in total county employment;
- $PPP2WdE = -\frac{PPP}{W\Delta E}$ is the ratio of the PPP loans normalized by the negative March-to-April change in county-level employment multiplied by W, the share of small businesses employment in total county employment.

[2] See https://www.census.gov/srd/www/x13as/ for details.

[3] An earlier version of the paper considered the ratio of PPP loans to total assets (PPP) for June 2020 is the key variable of interest, which does not allow to measure the effectiveness of PPP dollars relative to the labor market changes due to the onset of the COVID-19 recession. These results are qualitatively similar to the ones reported below and are available upon request.

The use of both unemployment and negative employment changes attempts to address potential changes in the composition of the labor force in response to the pandemic. Since the primary focus of the PPP was on small businesses with less than 500 employees, I also adjust these changes by the share of county-level employment in small businesses in total county-level employment as of the end of 2017, the last year when the U.S. Census Bureau Statistics of U.S. Businesses survey data were collected. When this quantity is used as an explanatory variable, it is designated by $SBweight$. Some counties experienced arbitrarily low changes in (un)unemployment between March and April 2020, inflating these ratios and warranting the use of winsorization at the first and 99^{th} percentiles. Finally, to facilitate the reporting of regression coefficients, these ratios are given in millions of dollars per job lost.

Third, demographic county controls from the U.S. Department of Agriculture include the latest available values for the percentage of county residents with bachelor's degrees ($BachPC$), log county-level population ($logPop$), percentage of residents with income below the poverty line ($PovPC$), log median county income ($logMedInc$). The COVID-19 pandemic had obvious deleterious medical implications and job loss could have particularly negative effects on access to health care, hence the inclusion of controls for county-level medical characteristics is warranted. These come from the 2019 County Health Rankings and include percentage of residents without health insurance ($UninsPC$) and percentage of residents whose health condition is either fair or poor ($FairPoorPC$). Table 1 presents the descriptive statistics for all variables' all available observations.

Fourth, institution-level banking variables from the FDIC Call Reports[4] are converted to their county-level counterparts using the branch-level FDIC Survey of Deposits.[5] Details of this conversion are available in the appendix. Importantly, the dataset includes the PPP loan balances from the June 2020 Call Reports totalling \$482 billion and reflecting the fact that loans under the program's aegis were primarily distributed through the banking system. Since total assets in the banking system were \$21.2 trillion, PPP loans accounted for about 2.3% of all assets. Banking controls include the standard measures that describe the overall health of a given institution and are considered by supervisors when they assign CAMELS ([C]apital adequacy, [A]sset quality, [M]anagment, [E]arnings, [L]iquidity, [S]ensitivity to market risk) ratings:[6] ratio of federal funds

[4] See `https://www7.fdic.gov/sdi/download_large_list_outside.asp`. Data are quarterly and availability starts in December 1992.

[5] See `https://www7.fdic.gov/sod/dynaDownload.asp`. Data are annual and availability starts in June 1994.

[6] See Bassett, Lee, and Spiller (2015) for motivation in using these banking variables as controls in empirical

sold less federal funds purchased to total assets (NFF), ratio of total equity capital to total assets ($Capital$), ratio of construction and development loans to total assets (CDL), ratio of commercial real estate loans to total assets (CRE), ratio of commercial and industrial loans to total assets (CI), net interest margin (NIM), ratio of non-interest expense to total income ($NIX2TR$), ratio of net chargeoffs to total loans and leases (NCO), ratio of brokered deposits to total assets (BRO). Since smaller counties frequently have only one participating institution, the Herfindahl-Hirschman Index, HHI, constructed from deposit concentrations and normalized to 1 (dividing the standard measure by 10,000) is also included.[7]

Table 1: Descriptive Statistics

Variable	1%	5%	10%	25%	50%	75%	90%	95%	99%	mean	st. dev.
PPP2WdE	-1.25	0.03	0.07	0.28	0.93	2.59	7.03	13.40	53.17	3.28	7.83
PPP2WdU	-4.20	0.04	0.12	0.45	1.40	4.02	12.37	23.99	107.37	5.81	15.12
PPP2dE	-1.93	0.01	0.04	0.15	0.51	1.48	4.47	8.98	34.65	2.03	5.06
PPP2dU	-6.65	0.02	0.06	0.24	0.78	2.44	8.00	16.99	88.93	4.01	11.99
Δ UR	-0.22	1.26	2.29	4.50	7.36	10.55	14.25	17.17	24.97	7.99	5.00
NFF	-4.42	-2.09	-1.15	-0.46	0.04	2.49	3.95	5.26	6.75	0.96	2.39
Capital	9.10	9.78	9.88	10.40	11.10	12.72	13.92	14.82	17.40	11.65	1.77
CDL	2.75	5.27	6.84	9.51	12.03	15.79	19.01	22.23	26.22	12.69	4.89
CRE	0.27	0.59	0.71	1.10	2.01	3.91	6.79	8.46	11.48	2.90	2.67
CI	1.97	2.85	3.72	5.38	7.50	15.60	22.15	25.68	31.37	10.69	7.40
NIM	1.52	2.21	2.50	2.66	2.80	3.28	3.64	3.90	4.67	2.96	0.62
NIX2TR	36.56	43.72	45.35	47.85	50.87	54.01	58.41	62.09	69.97	51.40	5.99
NCO	-0.01	0.03	0.05	0.14	0.29	0.39	0.48	0.57	1.04	0.30	0.27
BRO	0.00	0.00	0.11	1.37	3.29	6.18	6.87	7.29	21.61	3.95	3.71
HHI	0.01	0.01	0.02	0.03	0.06	0.14	0.31	1.00	1.00	0.15	0.23
BachPC	8.80	10.90	12.30	15.10	19.40	26.10	34.50	40.78	53.60	21.73	9.47
logPop	6.79	7.93	8.53	9.32	10.19	11.20	12.46	13.32	15.15	10.35	1.61
PovPC	5.20	7.30	8.60	10.80	14.10	18.30	23.20	26.10	35.06	15.13	6.09
logMedInc	10.31	10.48	10.55	10.69	10.83	10.99	11.15	11.29	11.52	10.85	0.24
UninsPC	3.76	4.87	5.59	7.16	10.40	14.01	17.93	20.72	25.71	11.14	4.94
FairPoorPC	10.06	11.26	12.11	13.94	16.69	20.48	23.67	26.08	31.98	17.48	4.70
SBweight	0.29	0.39	0.43	0.49	0.58	0.71	0.82	0.88	0.94	0.60	0.15

Note: PPP is from the June 2020 Call Reports; Δ UR is the March-April change in the unemployment rate; all banking and demographic characteristics are as of December 2019.

exercises evaluating policy transmission.

[7] For a detailed discussion of the definition of this variable, see, for instance, Drechsler, Savov, and Schnabl (2017) who investigate the role of deposit HHI in the transmission of monetary policy.

3 The COVID-19 Recession and the PPP

The purpose of this section is threefold. First, it provides an overview of the rapidly developing literature evaluating PPP effectiveness, highlighting the differences in data structure and model design between existing papers and the present one. Second, it describes the economic environment before and during the COVID-19 recession both with respect to the county-level geography and time-series macroeconomic dynamics. Finally, it details the timing of the PPP implementation, connecting it to the empirical design laid out in the subsequent sections.

3.1 Emerging Literature on the PPP Effectiveness Evaluation

The advent of the COVID-19 recession elicited not only strikingly rapid policy response but also a virtually real-time evaluation of these policies by the academic community, with considerable focus turning to the PPP. The key difficulty in evaluating the program's impact is the lack of a comprehensive dataset describing borrowed amounts, firm and lender characteristics, and channels of transmission of PPP funds to individual borrowers and the broader macroeconomy. Therefore, the general strategy has been to isolate a particular aspect of the program's effects under a specific set of assumptions and extrapolate to the broader population. The present paper also follows this general approach, focusing on lender characteristics and geographic granularity as the features of the data that can be gainfully exploited.

In perhaps the earliest attempt to evaluate the PPP effectiveness, Bartik et al. (2020) evaluate the impact of the original $359b tranche of the PPP loans using the state-level data and find that PPP had a positive but statistically insignificant impact on employment. Similarly, Granja et al. (2020), who also use state-level data, do not find a significant impact on unemployment or other measures of economic activity. The latter work is particularly relevant for the first part of this paper, since an important part of their findings is that the PPP funds generally did not flow to the hardest hit areas. The first set of the empirical exercises conducted below confirms this finding at the higher, county level of geographic granularity. The latter aspect is important because states are considerably more heterogeneous geographic units than counties. In a simple bivariate framework, the relationship between the initial surge in unemployment and PPP loans per job lost is negative but small and becomes economically much larger (in absolute value) once county-level banking and demographic controls are introduced.

Several studies focus on the effect that borrower characteristics have on the decision to borrow from the program and PPP's effects on key variables of interest, such as employment. Cororaton and Rosen (n.d.) focus on the PPP borrowing by public firms, with the key advantage of high financial transparency of these borrowers and disadvantage of their take-up being only 0.2% of all PPP funds, hence generalizations to the full population can only be made with extreme caution. They show that public firm borrowers tend to have fewer assets and more employees and have well established relationships with banks and, the quarter after PPP, experienced lower sales and net income and issued more debt. Hubbard and Strain (2020) also have a firm-level empirical design but their Dun & Bradstreet dataset focuses only on loans over $150,000[8] and, more importantly, their measure of PPP exposure is an indicator of whether a business applied—but not necessarily received—a PPP loan over $150,000. They claim that the presence of unsuccessful applicants introduces an attenuation bias, hence their estimates are likely to be conservative, yet in practice the nature of the bias depends on the nature of firm characteristics' impact on the application approval decision. Regardless, while they find that the effect of PPP exposure on the log of employment is mostly positive (albeit negative for firms in particular size ranges), it is generally small, at less than 1%. Similarly, they find positive but economically negligible effects on financial health as measured by staying current on payments and on business closure. Autor et al. (2020) use a research design that is similar to Hubbard and Strain (2020) and has similar limitations: their measure of PPP exposure is based on firm *eligibility* for PPP loans. Using different sources of high-frequency payroll data from ADP and a difference-in-difference approach, Autor et al. (2020) find a substantial boost to employment of about 2-4.5% with the per-job cost of about $244,000. In contrast, using multiple data sources and a similar research design, Chetty et al. (2020) find that PPP's economic effect was relatively small and that the annual cost of a job preserved by the PPP to be about $377,000. While none of these studies hail PPP as a dramatic success, the scope of potential impact generally ranges from nil to mildly positive. In contrast, Doniger and Kay (2021) use firm-level data and a 10-day delay in PPP funding in some areas to suggest that the PPP had large effects: a 10% increase in the PPP size would have reduced unemployment by additional 2% nationally.[9] Firm-level studies, therefore, deliver a wide range of estimates of the program's effectiveness.

The second set of empirical exercises below contributes to this literature by using the local projections framework to study the changes in county-level unemployment rates in responses to

[8] This may be a significant limitation at the firm-level, particularly for studying the PPP effects on the smallest firms, but not at the aggregate level, since those loans amounted to less than 1% of the overall issuance.

[9] The main limitation of their data is that they assign loan amounts over $150,000 to size category midpoints, even though there is no reason to believe that within-category loan distribution is symmetric around the mean and uncorrelated with lender and borrower characteristics.

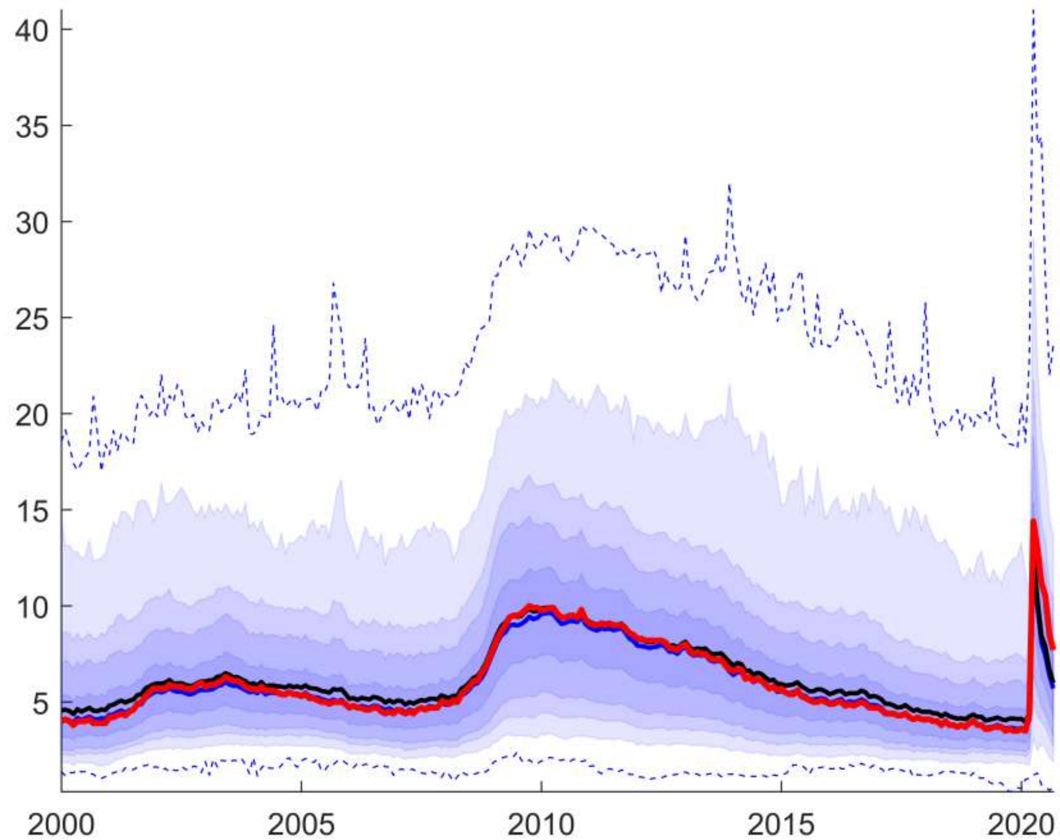


Figure 1: County-level and national seasonally adjusted unemployment rates

Note: Red line—national rate; blue line—county median rate; percentile bands (from darkest to lightest)—25/75, 10/90, 5/95, 1/99; dashed lines—maximum/minimum.

PPP lending per job lost. Intuitively, higher spending—with appropriate banking and demographic controls—should have resulted in larger unemployment declines. In the standard setting that does not allow for heterogeneity in the transmission of PPP lending to unemployment rates, this result does *not* hold: Changes in unemployment rates respond *positively* (and statistically significantly) to PPP loans per job lost, although this effect is economically negligible. However, introducing county-level heterogeneity by means of state-dependent local projection impulse responses, suggests that the PPP actually was quite effective in reducing unemployment, hence the program as a whole may be viewed as conditionally successful in areas whose characteristics were conducive to its transmission through local economies.

3.2 PPP and the Economic Environment

As described in the introduction, the onset of the COVID-19 pandemic resulted in an unprecedented disruption of the US labor market. Figure 1 provides the historical context for the evolution of county unemployment rates, as well as the national unemployment rate, seasonally adjusted before the pandemic onset. There is considerable heterogeneity in the levels of unemployment across the United States counties, both during normal times and recessions. While the national unemployment rate peaked at 14.7% in April 2020, its value registered a high of 41% in Cheboygan County, Michigan and a low of 1.2% in Loving County, Texas. Relative to March 2020, the national unemployment rate increased by over 10 percentage points, with exceptionally pronounced regional heterogeneity: Cheboygan County, Michigan posted a high of a 33.75 percentage point increase, whereas Tensas Parish, Louisiana registered a *decrease* of 4.21 percentage points. Importantly, April 2020 marked the largest increase in the dispersion of unemployment rates and their month-over-month changes since 1990.

Figure 2 maps the geography of county unemployment rate changes between March and April 2020. The geographical center of the country generally experienced only minor increases and in many cases decreases in unemployment, whereas the West Coast and the Midwest registered the largest increases. Insofar as the PPP was intended to mitigate the worst increases in unemployment, one would expect to see a similar geographical pattern in the distribution of the ratio of PPP loans per job lost at the county level.

Figure 3 provides the description of the distribution of the PPP lending per job lost. Not only does the geographical pattern established in Figure 2 not hold, it apparently reverses as the least hard hit counties in the middle of the country appear to have the highest concentrations of PPP loans, whereas some of the hardest hit counties on both coasts and the Midwest have much lower PPP funding per job lost. This pattern is consistent across all four measures of the PPP funding per job lost.

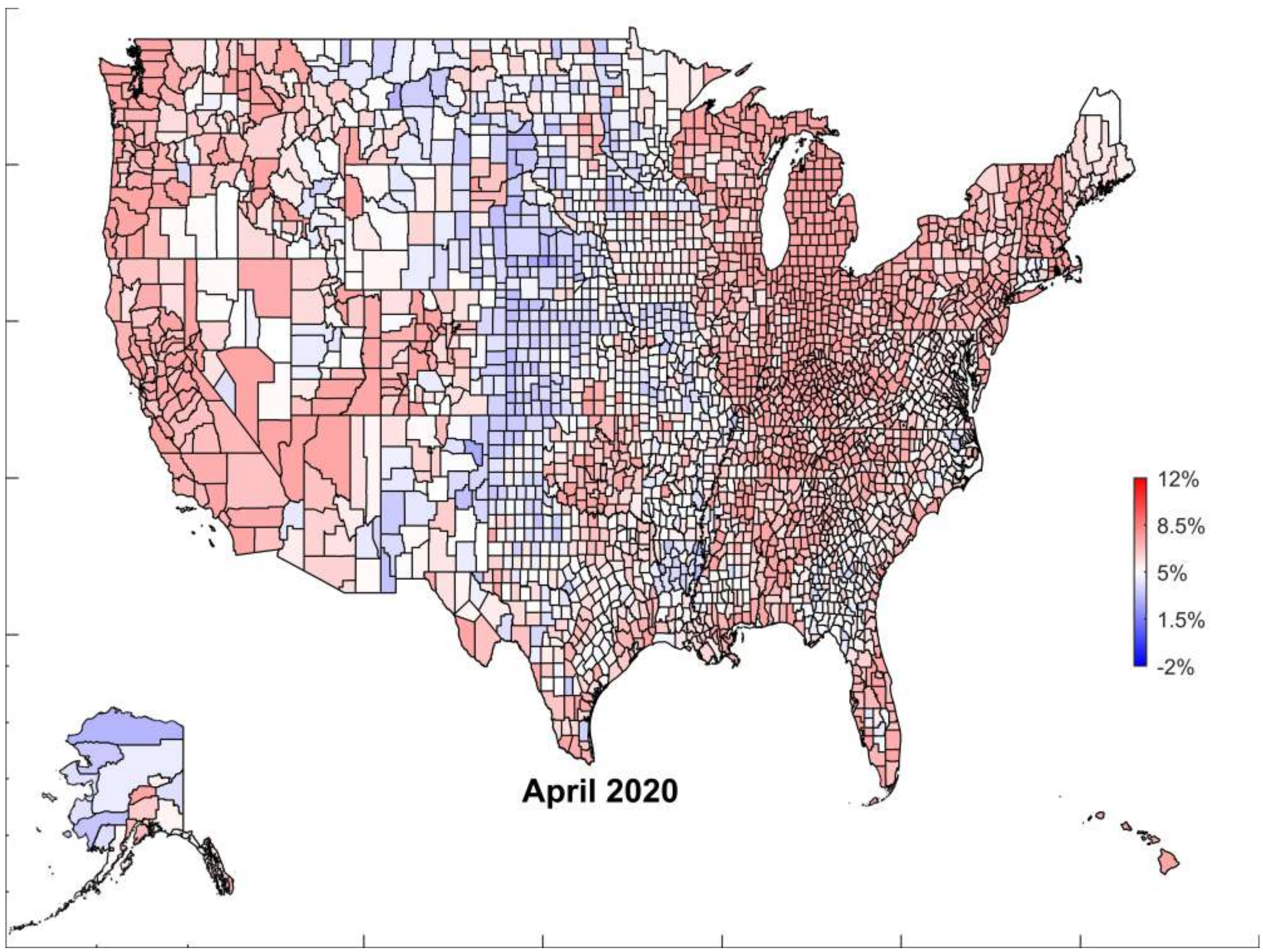
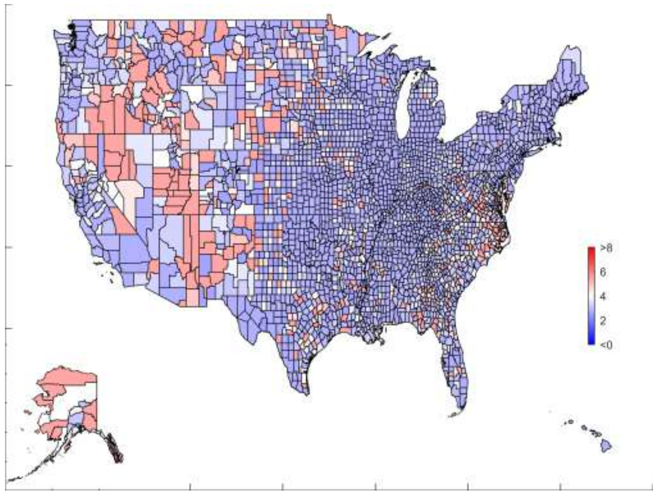
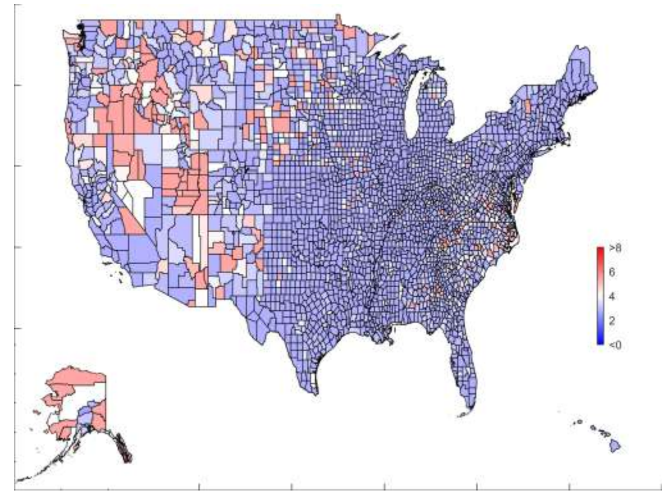


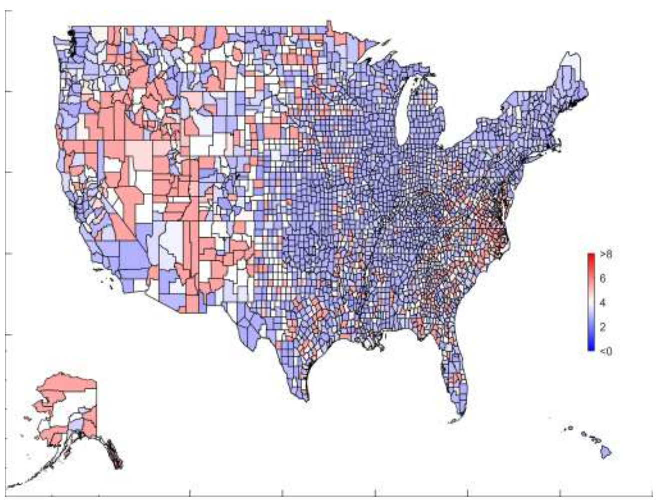
Figure 2: Change in the county unemployment rates between March and April 2020.



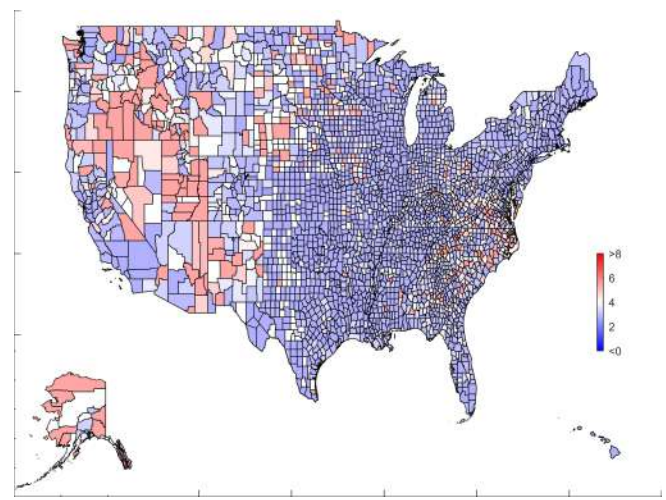
(a) $PPP2dU$



(b) $PPP2dE$



(c) $PPP2WdU$



(d) $PPP2WdE$

Figure 3: Geographical distribution of various ratios of PPP loans per job lost.

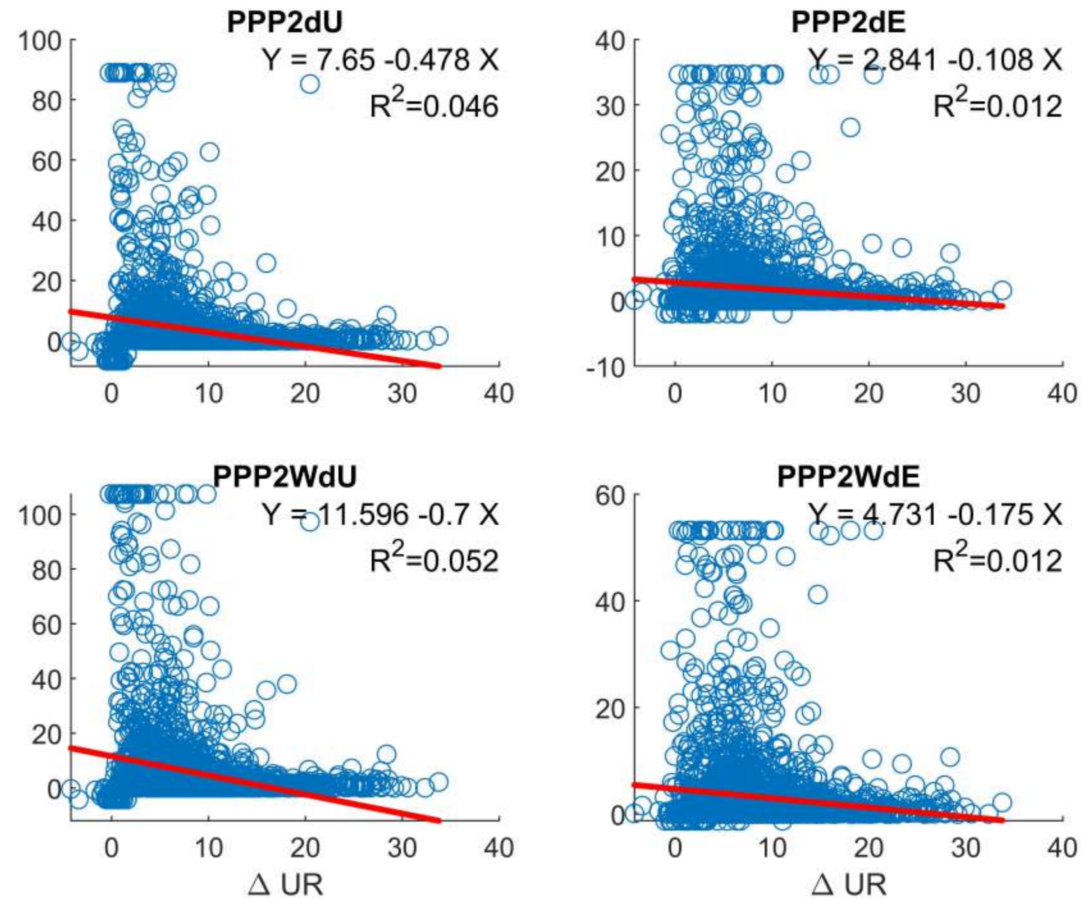


Figure 4: Bivariate relationships between the COVID-19 surge in unemployment and PPP loans per job lost.

Figure 4 provides a visual representation of the bivariate distribution of the initial surge in unemployment rates (on the horizontal axis) and the alternative ratios of PPP loans per job lost (vertical axis). The simple linear models have negative slope coefficients that are statistically significant at the 1% level with low Rs-squared between 0.012 and 0.052. Some of the observations, including the winsorized ones, are likely driven by local idiosyncrasies, as some counties had negligible and, in a couple of cases, no changes in (un)employment. However, despite strong pairwise negative relationships between PPP loan per job lost ratios and the initial surge in unemployment rates, suggesting that the PPP loans did not flow to the areas hardest hit by unemployment, the banking and demographic characteristics of individual counties may have an effect on how responsive different local businesses were to taking advantage of the PPP lending opportunities. The next section explores this specific issue in detail.

3.3 Timing of the PPP Implementation

As laid out in the introduction, the two key pieces of legislation that defined the PPP were the March 27, 2020, the Coronavirus Aid, Relief, and Economic Security Act (the CARES Act) that provided $350 billion in forgivable loans to small businesses, administered and guaranteed by the Small Business Adminstration (SBA), and the April 24, 2020 Paycheck Protection Program and Health Care Enhancement (PPPHCE) Act that increased the PPP funding to $669 billion.[10] The temporal proximity of these two pieces of legislation allows to treat the funding made available through the PPP as a single policy action.[11]

PPP implementation was also swift and channeled the vast majority of available funds through the banking system. On March 31, 2020, the SBA published borrower guidelines for the PPP[12], explaining the application process, terms, and conditions for loan forgiveness. Small businesses and sole proprietors could begin the application process starting on April 3 and independent contractors and self-employed individuals on April 10. Loan forgiveness was conditioned on maintaining existing payrolls or rehiring workers quickly while maintaining their salary levels. If payroll or salaries declined, the forgiven amount would decline as well. Two-year loans were available at 1% interest and could be obtained through existing SBA 7(a) lenders or federally insured banks or credit unions or participating Farm Credit System institutions.[13] When disbursed through depository institutions, the borrowed funds would typically get deposited into the deposit account of the small business borrower, in part because, as Hubbard and Strain (2020) point out, banks focused their lending efforts on existing customers, believing that this would minimize their risk exposure.[14] Lenders were incentivized to participate through a generous fee structure that ranged between 1% for loans above $2 million and 5% for loans under $350,000. According to the June 30, 2020 SBA report,[15] almost $500 billion of the PPP loan disbursements were distributed through the banking system, with credit unions coming a distant second with $9 billion. Therefore, an assessment of the program's effectiveness through the lens of the banking data is nearly comprehensive.

[10]Full text of the CARES Act is available at https://www.govinfo.gov/content/pkg/PLAW-116publ136/html/PLAW-116publ136.htm. Full text of the Paycheck Protection Program and Health Care Enhancement Act is available at https://www.govinfo.gov/content/pkg/PLAW-116publ139/html/PLAW-116publ139.htm.

[11]Re-authorization of the PPP in January 2021, on the other hand, should be viewed as a separate policy action implemented by a different presidential administration.

[12]The original document is available at https://home.treasury.gov/system/files/136/PPP--Fact-Sheet.pdf.

[13]See the text of the March 31, 2020, U.S. Treasury announcement at https://home.treasury.gov/system/files/136/PPP%20--%20Overview.pdf.

[14]See Strand and Stewart (2020) for additional evidence.

[15]See https://www.sba.gov/sites/default/files/2020-07/PPP%20Results%20-%20Sunday%20FINAL.pdf.

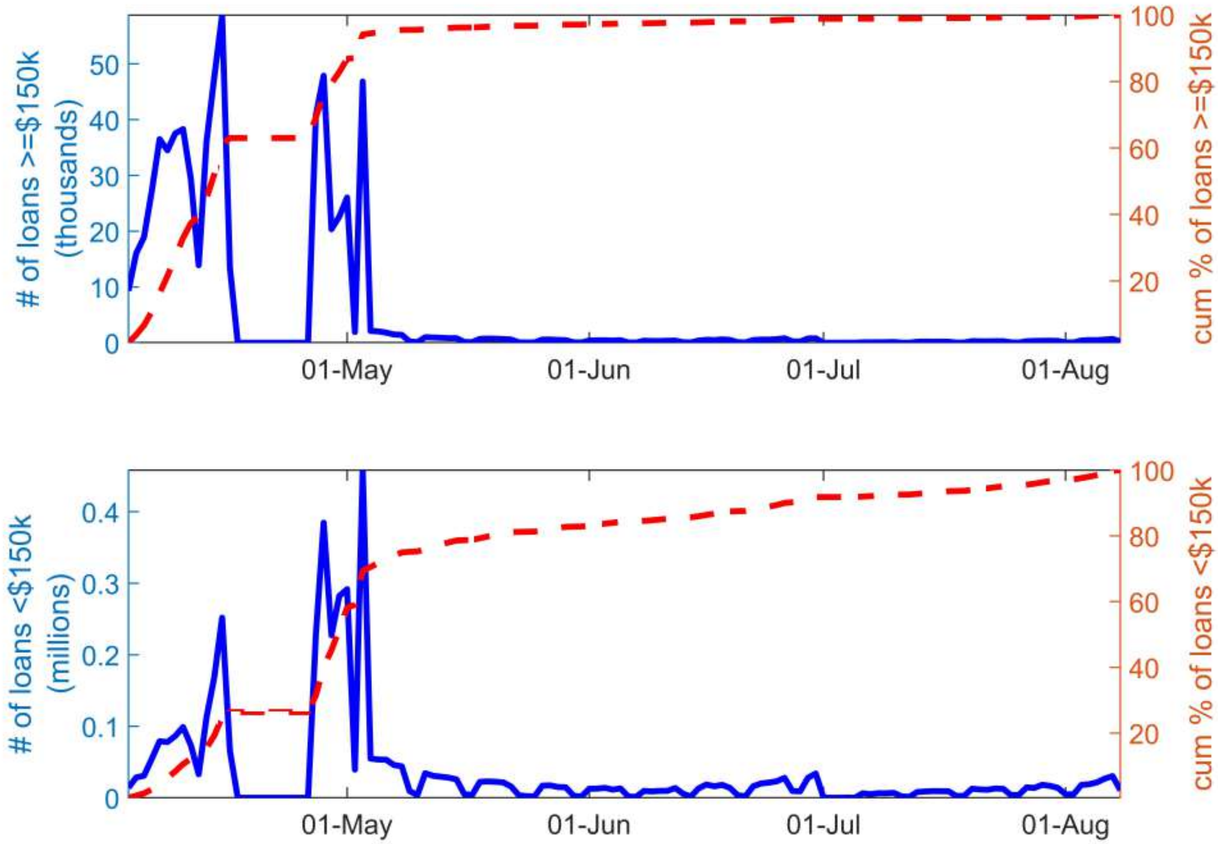


Figure 5: Number of loans approved per day (left axis) and cumulative shares of loans approved (right axis) out of the PPP total

Note: Top panel: loans over $150,000, in thousands of loans per day; bottom panel: loans under $150,000, in millions of loans per day.

Figure 5 describes the timing of the loan approval process using the SBA data.[16] Importantly, while the dollar amounts for loans under $150k are reported, loans over $150k are reported in buckets of $5-10 million (m), $2m-5m, $1m-2m, $350,000-1m, and $150,000-$350,000 making granular analysis of the loan data impossible. Reflecting the timing of the CARES and PPPHCE Acts, PPP loans were approved in two large waves: during the first two weeks of April and during the last week of April and the first week of May. By May 3rd, over 95% of all PPP loans over $150,000 and about 80% of the loans under $150,000 were distributed, with negligible approval rates and amounts after May 31. Therefore, the relevant determinants of the loan distribution process can be taken as of May 2020 at the latest and its effects measured from June onwards.

[16]Loan specific data are available at https://www.sba.gov/funding-programs/loans/coronavirus-relief-options/paycheck-protection-program.

Finally, the main reason for using the standard methodology for obtaining county-specific values for PPP loans is the lack of loan-specific information for loans of at least \$150,000. While this information is available for loans under \$150,000, allowing for their geography to be traced at the zipcode level, their total amount in the SBA dataset is less than \$4.5 billion or less than 1% of all disbursed funds. Large loans, on the other hand, are reported in relatively large buckets, precluding the exact disentangling of their geography.

4 Determinants of County-level PPP Loan per Job Lost Ratios

This section estimates several specifications that model PPP loan per job lost ratios as functions of the initial unemployment surge in March-April 2020, ΔUR, a vector of banking conditions, $\mathbf{B}$, and demographic characteristics, $\mathbf{D}$, both taken at pre-pandemic levels as of December 2019, given by the following:

$$PPP2x_c = a + \beta \Delta UR_c + \mathbf{B}_c \Gamma + \Theta \mathbf{D}_c \Gamma, \tag{1}$$

and $PPP2x$ refers to one of four measures of PPP loans per job lost with x designating the specific denominator used in the construction of the relevant ratio as described in Section 2.

Table 2 presents estimation results for four specifications. As in the bivariate models in Figure 4, the introduction of banking and demographic controls does not change the negative relationship between the initial surge in unemployment and the four PPP loan per job lost ratios. In fact, the absolute values of the slope coefficients become larger and are significant at the 1% level for three out of four measures and at the 5% level for the fourth one, $PPP2WdU$. This finding suggests that the PPP funds did not flow to the areas hardest hit by unemployment and those areas received relatively small amounts of PPP funding per job lost.

The coefficients on the banking and demographic regressors provide additional insights for understanding the direction of PPP loan flows. The banking variables that have statistically significant coefficients in all four specifications suggest that the PPP loans primarily flowed to counties whose banks were relatively risky and had low levels of capital, high levels of C&I loan concentration, low net interest rate margins, high levels of net charge-offs, high levels of brokered deposits, and relatively high cash positions accumulated by trading federal funds on the eve of the pandemic. High levels of deposit concentration measured by the HHI also have a positive coefficient, suggesting that the PPP loans flowed primarily through banks that faced low levels of banking competition.

Demographic regressors also paint a consistent picture across all four specifications. PPP loans

Table 2: Determinants of PPP Concentration

	PPP2WdE	PPP2WdU	PPP2dE	PPP2dU
Constant	-84.572***	2.215	-81.825**	0.986
	(30.345)	(11.498)	(37.974)	(19.708)
Δ UR	-0.344***	-0.048**	-0.540***	-0.094***
	(0.049)	(0.019)	(0.064)	(0.030)
NFF	0.409***	0.205***	0.593***	0.348***
	(0.106)	(0.046)	(0.150)	(0.072)
Capital	-0.412***	-0.219***	-0.504***	-0.326***
	(0.133)	(0.066)	(0.189)	(0.108)
CDL	-0.202**	-0.035	-0.271**	-0.088
	(0.102)	(0.037)	(0.137)	(0.059)
CRE	-0.023	-0.026	-0.052	-0.041
	(0.043)	(0.021)	(0.063)	(0.033)
CI	0.248***	0.100***	0.356***	0.172***
	(0.047)	(0.018)	(0.066)	(0.030)
NIM	-4.570***	-2.623***	-6.721***	-4.252***
	(0.565)	(0.327)	(0.846)	(0.540)
NIX2TR	-0.076**	-0.019	-0.074	-0.023
	(0.036)	(0.016)	(0.050)	(0.026)
NCO	2.351**	1.779***	3.249**	2.674***
	(1.016)	(0.522)	(1.469)	(0.847)
BRO	0.181***	0.075**	0.247***	0.119**
	(0.060)	(0.030)	(0.083)	(0.049)
HHI	13.911***	5.094***	18.591***	8.461***
	(2.748)	(1.104)	(3.432)	(1.758)
BachPC	-0.037	0.012	-0.018	0.016
	(0.035)	(0.013)	(0.045)	(0.023)
logPop	-2.894***	-1.539***	-4.607***	-2.753***
	(0.289)	(0.130)	(0.388)	(0.219)
PovPC	0.541***	0.163***	0.711***	0.294***
	(0.121)	(0.047)	(0.152)	(0.078)
logMedInc	12.357***	2.228**	14.954***	4.381**
	(2.906)	(1.034)	(3.559)	(1.790)
UninsPC	0.233***	0.088***	0.316***	0.153***
	(0.054)	(0.021)	(0.069)	(0.035)
FairPoorPC	-0.200**	-0.110***	-0.261**	-0.185***
	(0.085)	(0.038)	(0.123)	(0.063)
SBweight	-4.741**	-1.737*	-16.310***	-9.204***
	(2.086)	(0.900)	(2.913)	(1.548)
DoF	2917	2917	2917	2917
$\bar{R}^2$	0.241	0.241	0.269	0.263

Note: Robust standard errors are in parentheses. Asterisks designate statistical significance: ***—at the 1% level; **—at the 5% level; *—at the 10% level.

per job lost were higher in smaller counties as evidenced by the negative coefficients on $logPop$. they were also higher in counties with high shares of population below the poverty line ($PovPC$) yet ones that had high levels of median income per capita ($logMedInc$), which suggests that counties with larger levels of income inequality may have received relatively large amounts of PPP loans per job lost. Counties with high shares of people without medical insurance ($UninsPC$) and counties with low shares of residents whose health was fair or poor ($FairPoorPC$) received higher PPP loan volumes. Interestingly, counties with relatively large shares of the workforce engaged in small businesses ($SBweight$) received smaller amounts of PPP loans per job lost, which may be explained by the possibility that large shares of engagement in small businesses generally occur in areas where these businesses have relatively few employees.

Which variables are most useful in explaining the variation in cross-county PPP concentrations? One way to characterize the extent to which individual regressors contribute to the linear model's R^2 is to start with the encompassing model and then consider a weighted average of R^2's from all models nested in the encompassing one that contain that particular regressor. This is the idea behind the so-called Shapley-Owen decomposition that calculates the partial R^2 due to the j^{th} variable out of K total regressors as:

$$R_j^2 = \sum_{T \subset X - \{x_j\}} \frac{R^2(T \bigcup \{x_j\}) - R^2(T)}{K * C(k-1, K_T)}, \tag{2}$$

where X is the set of K regressors, $x_1, \ldots, x_j, \ldots, x_K$, T is some subset of X that does not contain x_j with K_T regressors in it.[17] Intuitively, the partial R-squared from this decomposition provides a weighted average of the differences between models nested in the encompassing one with and without the regressor of interest. Since all K partial Rs-squared add up to the ordinary R-squared for the regression, it is straightforward to calculate each variable's contribution to the overall R-squared of the encompassing model with all of the percentage contributions adding up to 100%.

Table 3 provides the results of this decomposition where the encompassing model is given by (1). The top two factors in explaining variation in the four dependent variables are $logPop$ and HHI, suggesting that county population size and the lack of banking competition both had strong negative effects on the availability of PPP loans per job lost. Other notable contributions towards explaining the variation in dependent variables are NIM and ΔUR. Banks with low profitability may have been particularly interested in the fees generated by participating in the PPP. The large

[17] See Redell (2019) for a broad methodological discussion and Israeli (2007) for a recent application.

Table 3: Shapley-Owen Decomposition of PPP Concentration Models

	PPP2WdE	PPP2WdU	PPP2dE	PPP2dU
Δ UR	13.6	3.2	14.6	3.5
NFF	1.7	2.2	1.6	2.2
Capital	1.7	2.7	1.3	2.2
CDL	2.8	3.7	2.8	3.9
CRE	2.5	4.4	2.6	4.3
CI	2.3	2.6	2.5	2.9
NIM	11.3	20.0	12.3	19.4
NIX2TR	0.4	0.3	0.3	0.3
NCO	0.8	1.4	0.8	1.3
BRO	2.4	2.4	2.1	2.1
HHI	21.1	15.1	17.7	14.3
BachPC	1.4	1.5	1.4	1.5
logPop	24.0	31.5	25.1	30.5
PovPC	3.7	1.9	3.5	2.1
logMedInc	2.8	1.5	2.2	1.5
UninsPC	5.2	2.8	4.5	2.7
FairPoorPC	0.9	1.0	1.0	0.9
SBweight	1.4	1.7	3.7	4.5
R^2	0.240	0.239	0.268	0.261

Note: Values are each variable's percentage contributions to the ordinary R^2 listed in the bottom row.

differential in the contributions of the in the denominator rather than negative employment change, suggests that changes in the labor force dynamics also had an effect on the distribution of the PPP loans. Finally, other explanatory variables contribute relatively small shares towards explaining the dependent variable variation across specifications with their percentage shares of Rs-squared remaining in the low single digits.

5 Effects of PPP Participation on Unemployment Rates

This section considers the dynamic effect of the PPP loan concentration on county unemployment rates relative to April 2020 using the local projection impulse response framework originally developed by Jorda (2005). The results presented below suggest that the effectiveness of the PPP loan disbursement needs to be considered adjusting for the local county-level conditions. The setting that does not allow for impulse responses to be in part driven by local characteristics shows that the program was very ineffective: Counties with high PPP loans per job lost experienced subsequently higher unemployment rates and this effect is statistically significant across specifications. The state-dependent impulse response setting of the second subsection reverses this result: PPP exposure resulted in large subsequent decreases in unemployment, albeit with considerable heterogeneity driven by both banking and demographic factors.

5.1 Unemployment Rate Changes: Linear Case

Under the linear local projections approach, one can map out the impulse response functions (IRFs) of the change of county-level unemployment rates relative to the initial COVID-related surge first reflected in the April 2020 numbers as follows:

$$UR_{c,Apr2020+h} - UR_{c,Apr2020} = a_h + b_h PPP2x_c + \mathbf{B}_c G_h + \mathbf{D}_c F_h. \tag{3}$$

Here, h is the projection or impulse response horizon and b_h are the coefficients that map out these impulse responses and $\mathbf{B}$ and $\mathbf{D}$ are banking and demographic controls, respectively, as in (1). While the discussion of the PPP loan distribution time line leaves some ambiguity in terms of interpreting the results of the May 2020 unemployment to PPP, since the PPPHCE took the distribution efforts into May, there is little ambiguity for the subsequent months. Hence only the $h = 0$ results may suffer from endogeneity whereas their $h > 0$ counterparts should be free from it.

Table 4 presents the IRFs from estimating alternative specifications of equation (3). Surprisingly, counties with large volumes of PPP loans per job lost subsequently experienced higher unemployment. This result is robust across the four specifications and is economically small. Taking 0.04 as the estimate of the effect of $PPP2x$ on the unemployment rate 3 to 5 months out, counties in the 90^th percentile of the $PPP2x$ distribution, depending on the specific measure, could experience higher unemployment rate between 0.2 and 0.4 percentage points higher than counties with median levels of PPP funding. However, the sheer positive effect and its statistical significance

Table 4: Impulse Responses of Unemployment Rate Change to PPP Concentration

	PPP2WdE	PPP2WdU	PPP2dE	PPP2dU
May 2020, $h = 1$	0.023***	0.012	0.021***	0.018**
	(0.005)	(0.011)	(0.003)	(0.008)
June 2020, $h = 2$	0.046***	0.028*	0.040***	0.028***
	(0.006)	(0.017)	(0.004)	(0.010)
July 2020, $h = 3$	0.057***	0.052***	0.049***	0.043***
	(0.007)	(0.019)	(0.005)	(0.012)
August 2020, $h = 4$	0.049***	0.025	0.043***	0.024**
	(0.007)	(0.019)	(0.005)	(0.012)
September 2020, $h = 5$	0.053***	0.043**	0.048***	0.035***
	(0.008)	(0.019)	(0.005)	(0.012)

Note: Robust standard errors are in parentheses. Asterisks designate statistical significance: ***—at the 1% level; **—at the 5% level; *—at the 10% level.

raises concerns about the program's effectiveness in mitigating labor market disruptions due to the pandemic. The next subsection addresses this concern in a state-dependent impulse response framework.

5.2 Unemployment Rate Changes: State-dependent Case

To assess the specific determinants of the effectiveness of the PPP loan concentration transmission to unemployment, I modify equation (3) to allow for state-dependent local projections impulse responses via interaction terms:[18]

$$UR_{c,Apr2020+h} - UR_{c,Apr2020} = a_h + b_h PPP2x_c + \mathbf{B}_c G_h + \mathbf{D}_c F_h + \mathbf{B}_c \bigodot PPP2x_c H_h + \mathbf{D}_c \bigodot PPP_c J_h, \tag{4}$$

where $\bigodot$ indicates that each column of $\mathbf{B}$ or $\mathbf{D}$ is multiplied by $PPP2x$. In (4), the dynamic effect of PPP loans per job lost on changes in the unemployment rate now becomes a function of the underlying county-level initial (as of 2019Q4) banking and demographic characteristics, allowing for heterogeneity in PPP transmission across different counties.

Table 5 presents the estimation results from this exercise, dropping the coefficients that are not directly associated with PPP-related terms for parsimony. Several interesting features emerge. First, the coefficients on $PPP2x$ are negative in all specifications, across all horizons, and are economically large. While they are not always statistically significant at conventional levels, all specifications have at least one coefficient that is significant at the 5% level and all specifications'

[18]For an early application of this methodology, see Auerbach and Gorodnichenko (2013) who study state-dependent local projections impulse responses to fiscal shocks.

coefficients are significant in June 2020, suggesting that the PPP had an immediate impact on stabilizing labor market conditions.

Second, banking conditions, with the possible exception of liquidity captured by $PPP2x*NFF$, did not appear to have material effect on the transmission of PPP loans to labor market conditions. Both $PPP2dU$ and $PPP2WdU$ specifications show protracted declines in unemployment rates in counties where banking institutions had high ratios of net federal funds to total assets before the onset of the COVID-19 Recession. (The effects are short-lived for the $PPP2dU$ and $PPP2WdU$ specifications.) This result is perhaps the strongest among the banking characteristics and is not surprising given the recent literature on bank liquidity hoarding. Berger et al. (2021) find that liquidity hoarding increases in response to, and hence may be symptomatic of, economic policy uncertainty; hence banks with large liquidity buffers may have been more willing to engage in the PPP program in areas where it could make a larger difference. At longer horizons, $PPP2x * BRO$ becomes significant and positive, again implying that banks with stronger liquidity (and hence lower brokered deposit ratios) were able to intermediate PPP loans more efficiently.

Third, demographic conditions had a strong effect on the transmission of PPP loans to the labor markets. $PPP2x * BachPC$ coefficients are negative and significant at the 1% level across all specifications and horizons, suggesting that the program may have been more effective in areas with relatively educated labor force. $PPP2x * logPop$ coefficients are positive and, with one exception, significant at least at the 5% level, implying that the PPP was more effective in counties with smaller populations.

6 Concluding Remarks

The main contribution of this paper is to provide a framework that nests much of the available results on the determinants of the geographical distribution of the PPP loan concentration and its effect on economic activity via a state-dependent local projection modeling framework. Much like Granja et al. (2020), it finds that the PPP funds did not flow to the hardest hit areas. These results appear in the simple bivariate framework and become even stronger with the addition of different controls for county-level heterogeneity. Similar to existing studies, it uses the standard local projections framework to show that the PPP effects on the subsequent changes in the unemployment rates were, counterintuitively, positive and statistically significant, albeit economically small. Modifying this framework to allow for state-dependent transmission of the PPP effects reverses this result: PPP effects become quite strong in reducing subsequent unemployment—both economically and in terms of statistical significance. As the literature on PPP effectiveness continues to move forward, it is important to control for local conditions.

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A Construction of County-level Banking Variables

The following variables are downloaded from the FDIC public Call Reports dataset: *cert* (FDIC certificate number for a depository institution), *asset* (total assets), *frepo* (federal funds sold and reverse repurchase), *frepp* (federal funds purchased and repurchase agreements), *eqtot* (total equity capital), *lnrecons* (construction and development loans), *lnrenres* (loans secured by nonfarm non-residential properties), *lnci* (commercial and industrial loans), *lnlsgr* (total loans and leases), *nim* (net interest income), *nonix* (total noninterest expense), *intinc* (total interest income), *nonii* (total noninterest income), *ntlnls* (net charge-offs), *bro* (brokered deposits), and *ppplnbal* (outstanding balance of PPP loans). To be able to construct county-level versions of these banking variables, branch-level deposits ($DEPSUMBR$) and branch identifiers ($UNINUMBR$) were downloaded from the FDIC Survey of Deposits as of June 2019. County-level banking variables were constructed using the following algorithm where b is the branch identifier, i is the bank identifier, c is the county identifier, and t is the quarter identifier:

1. Construct weights for a bank b's presence in county c as the share of its deposits D_{bc} in the county's total deposits D_c:
$$w_{ic} = \frac{D_{ic}}{D_c} = \frac{\sum_b D_{bic}}{\sum_i D_{ic}}.$$
2. For any Call Report variable for bank i at time t, construct the county-level equivalent as:
$$X_{ct} = \sum_{i=1}^{I_{ct}} w_{ic} X_{it}.$$
3. Use accounting definitions to construct county-level banking variables used for estimation.

Below is the list of banking variables used in estimation (with CAMELS category in parentheses):

- Net federal funds position (liquidity): $NFF = \frac{(frepo_{ct} - frepp_{ct})}{asset_{ct}} * 100$
- Total equity capital ratio (capital): $Capital = \frac{eqtot_{ct}}{asset_{ct}} * 100$
- Construction and development loan concentration (management): $CDL = \frac{lnrecons_{ct}}{asset_{ct}} * 100$
- Commercial real estate concentration (management): $CRE = \frac{lnrenres_{ct}}{asset_{ct}} * 100$
- Commercial and industrial loan concentration (management): $CI = \frac{lnci_{ct}}{asset_{ct}} * 100$
- Net interest margin (earnings): $NIM = \frac{nim_{ct}}{asset_{ct}} * 100$

- Noninterest expense to total revenue (management): $NIX2TR = \frac{nonix_{ct}}{(intinc_{ct}+nonii_{ct})} * 100$
- Net-chargeoff rate (asset quality): $NCO = \frac{ntlnls_{ct}}{lnlsgr_{ct}} * 100$
- Brokered deposits share (liquidity): $BRO = \frac{bro_{ct}}{asset_{ct}} * 100$
- PPP loan concentration: $PPP = \frac{ppplnbal_{ct}}{asset_{ct}} * 100$
- Herfindahl-Hirschman Index: $HHI = \frac{\sum_b (D_{bct} * 100)^2}{B_{ct} D_{ct}^2} / 10,000$, where $D_{ct} = \sum_b D_{bct}$ are total deposits in county c at time t, B_{ct} is the total number of banks in county c at time t, $D_{bct} = \sum_r D_{rbct}$ are the total deposits of bank b in county c at time t across its branches r. The HHI is normalized by 10,000 to range between 0 and 1 to yield more easily interpretable coefficients in tables with regression results.

PPP is taken as of June 2020 and all other banking characteristic controls are as of December 2019.

Table 5: Impulse Responses of Unemployment Rate Change to PPP Concentration, with Interaction Terms

	PPP2x Denominator																			
Variable	dU	dE	WdU	WdE	dU	dE	WdU	WdE	dU	dE	WdU	WdE	dU	dE	WdU	WdE	dU	dE	WdU	WdE
	May 2020, $h = 1$				June 2020, $h = 2$				July 2020, $h = 3$				August 2020, $h = 4$				September 2020, $h = 5$			
PPP2x	-0.599	-0.572	-0.507*	-0.645	-1.161**	-2.870**	-0.860**	-1.846**	-0.959	-2.212	-0.746*	-1.848**	-1.143*	-1.877	-0.860**	-1.788*	-0.808	-0.252	-0.575	-0.899
	(0.400)	(0.967)	(0.294)	(0.642)	(0.570)	(1.372)	(0.382)	(0.799)	(0.637)	(1.538)	(0.417)	(0.901)	(0.643)	(1.631)	(0.427)	(0.960)	(0.654)	(1.581)	(0.437)	(0.924)
PPP2x*NFF	-0.010***	-0.033*	-0.009***	-0.028**	-0.012**	-0.033	-0.009***	-0.028**	-0.011**	-0.025	-0.010**	-0.021	-0.015**	-0.012	-0.015***	-0.018	-0.017***	-0.019	-0.016***	-0.020
	(0.004)	(0.019)	(0.003)	(0.012)	(0.005)	(0.022)	(0.003)	(0.014)	(0.006)	(0.029)	(0.004)	(0.018)	(0.006)	(0.038)	(0.004)	(0.024)	(0.006)	(0.036)	(0.004)	(0.022)
PPP2x*Cap	0.008**	-0.007	0.004	-0.002	0.013***	0.014	0.008**	0.012	0.017***	0.022	0.011**	0.022	0.017***	0.017	0.012***	0.017	0.017***	0.008	0.011**	0.011
	(0.004)	(0.013)	(0.003)	(0.009)	(0.005)	(0.018)	(0.003)	(0.012)	(0.006)	(0.023)	(0.004)	(0.015)	(0.006)	(0.025)	(0.004)	(0.017)	(0.006)	(0.025)	(0.004)	(0.017)
PPP2x*CDL	0.001	-0.010	0.000	-0.005	-0.001	-0.018**	-0.001	-0.010*	0.000	-0.017	-0.000	-0.007	0.002	-0.008	0.000	-0.003	0.002	-0.007	0.001	-0.002
	(0.002)	(0.007)	(0.001)	(0.005)	(0.002)	(0.008)	(0.001)	(0.005)	(0.002)	(0.011)	(0.001)	(0.007)	(0.002)	(0.013)	(0.001)	(0.008)	(0.002)	(0.012)	(0.001)	(0.008)
PPP2x*CRE	-0.001	-0.035	-0.003	-0.038**	0.001	-0.009	-0.002	-0.022	0.005	0.005	-0.000	-0.013	0.007	0.022	0.001	-0.004	0.007	0.019	0.001	-0.006
	(0.003)	(0.022)	(0.002)	(0.016)	(0.004)	(0.027)	(0.003)	(0.017)	(0.005)	(0.033)	(0.003)	(0.020)	(0.005)	(0.039)	(0.004)	(0.024)	(0.005)	(0.037)	(0.004)	(0.023)
PPP2x*CI	-0.000	0.013***	0.001	0.008***	-0.001	0.002	0.001	0.002	-0.002	0.003	-0.000	0.002	-0.003	0.005	-0.001	0.004	-0.003	0.003	-0.001	0.003
	(0.002)	(0.004)	(0.001)	(0.003)	(0.002)	(0.006)	(0.002)	(0.004)	(0.003)	(0.007)	(0.002)	(0.004)	(0.002)	(0.007)	(0.002)	(0.004)	(0.003)	(0.007)	(0.002)	(0.004)
PPP2x*NIM	-0.005	-0.071**	-0.008	-0.024	0.001	-0.034	-0.005	0.002	0.010	-0.031	0.003	0.013	0.008	-0.070	0.004	-0.016	0.013	-0.052	0.008	-0.005
	(0.014)	(0.036)	(0.009)	(0.025)	(0.019)	(0.047)	(0.012)	(0.029)	(0.022)	(0.053)	(0.014)	(0.033)	(0.021)	(0.054)	(0.013)	(0.034)	(0.021)	(0.054)	(0.014)	(0.033)
PPP2x*NIX2TR	0.001	0.005	0.001	0.004	0.005***	0.009	0.003***	0.006	0.005**	0.010	0.004**	0.007	0.006***	0.009	0.005***	0.006	0.007***	0.009	0.005***	0.006
	(0.001)	(0.004)	(0.001)	(0.003)	(0.002)	(0.006)	(0.001)	(0.004)	(0.002)	(0.007)	(0.002)	(0.005)	(0.002)	(0.008)	(0.001)	(0.005)	(0.002)	(0.007)	(0.002)	(0.005)
PPP2x*NCO	0.097**	0.250**	0.093**	0.186**	0.149**	0.194	0.147***	0.168	0.129	0.181	0.135**	0.171	0.131	0.127	0.144**	0.167	0.136*	0.080	0.144**	0.130
	(0.047)	(0.121)	(0.037)	(0.090)	(0.064)	(0.186)	(0.049)	(0.129)	(0.080)	(0.220)	(0.059)	(0.150)	(0.084)	(0.231)	(0.062)	(0.155)	(0.079)	(0.227)	(0.059)	(0.148)
PPP2x*BRO	0.000	0.001	0.000	-0.005	0.004	0.012	0.003	0.002	0.007***	0.024	0.006***	0.010	0.010***	0.034**	0.007***	0.016	0.009***	0.032*	0.006***	0.015
	(0.002)	(0.012)	(0.002)	(0.008)	(0.002)	(0.012)	(0.002)	(0.008)	(0.003)	(0.015)	(0.002)	(0.010)	(0.003)	(0.017)	(0.002)	(0.012)	(0.003)	(0.017)	(0.002)	(0.011)
PPP2x*HHI	-0.003	-0.013	0.003	0.014	-0.032	-0.077	-0.015	-0.018	-0.025	-0.059	-0.007	-0.005	-0.029	-0.053	-0.006	0.007	-0.010	-0.005	0.007	0.031
	(0.016)	(0.034)	(0.012)	(0.025)	(0.020)	(0.049)	(0.015)	(0.030)	(0.021)	(0.055)	(0.017)	(0.033)	(0.024)	(0.055)	(0.018)	(0.033)	(0.024)	(0.051)	(0.018)	(0.031)
PPP2x*BachPC	-0.001**	-0.006***	-0.001***	-0.004***	-0.003***	-0.011***	-0.002***	-0.006***	-0.003***	-0.010***	-0.002***	-0.006***	-0.003***	-0.013***	-0.003***	-0.008***	-0.003***	-0.012***	-0.002***	-0.007***
	(0.001)	(0.002)	(0.000)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)	(0.002)
PPP2x*logPop	0.018**	0.042***	0.020***	0.033***	0.030***	0.023	0.030***	0.024**	0.041***	0.060**	0.040***	0.050***	0.041***	0.060**	0.040***	0.053***	0.053***	0.090***	0.048***	0.069***
	(0.008)	(0.015)	(0.005)	(0.010)	(0.008)	(0.020)	(0.006)	(0.012)	(0.010)	(0.024)	(0.008)	(0.014)	(0.013)	(0.025)	(0.009)	(0.015)	(0.015)	(0.024)	(0.010)	(0.014)
PPP2x*PovPC	0.000	0.001	-0.000	0.001	-0.002	0.000	-0.002**	0.000	-0.004***	-0.005	-0.003***	-0.002	-0.003*	-0.003	-0.003**	-0.001	-0.005***	-0.010*	-0.004***	-0.004*
	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)	(0.004)	(0.001)	(0.002)	(0.001)	(0.004)	(0.001)	(0.002)	(0.002)	(0.004)	(0.001)	(0.002)	(0.002)	(0.004)	(0.001)	(0.002)
PPP2x*logMedInc	0.036	0.040	0.026	0.044	0.054	0.238**	0.036	0.138**	0.021	0.121	0.011	0.091	0.033	0.094	0.016	0.092	-0.010	-0.068	-0.018	0.004
	(0.035)	(0.085)	(0.026)	(0.054)	(0.047)	(0.118)	(0.032)	(0.065)	(0.052)	(0.127)	(0.035)	(0.068)	(0.053)	(0.130)	(0.036)	(0.070)	(0.056)	(0.125)	(0.038)	(0.067)
PPP2x*UninsPC	-0.000	-0.003	-0.000	0.000	-0.002	-0.009**	-0.001	-0.004	-0.006***	-0.018***	-0.004***	-0.008***	-0.006***	-0.021***	-0.004***	-0.010***	-0.006***	-0.022***	-0.005***	-0.011***
	(0.001)	(0.004)	(0.001)	(0.002)	(0.001)	(0.004)	(0.001)	(0.002)	(0.001)	(0.004)	(0.001)	(0.002)	(0.002)	(0.004)	(0.001)	(0.002)	(0.002)	(0.004)	(0.001)	(0.002)
PPP2x*FairPoorPC	-0.000	0.002	0.000	-0.002	0.005**	0.014**	0.003**	0.005	0.008***	0.023***	0.005***	0.010***	0.004*	0.018***	0.003**	0.006	0.005*	0.020***	0.004**	0.007*
	(0.002)	(0.006)	(0.002)	(0.004)	(0.002)	(0.006)	(0.001)	(0.003)	(0.002)	(0.006)	(0.002)	(0.003)	(0.003)	(0.006)	(0.002)	(0.004)	(0.003)	(0.006)	(0.002)	(0.003)
PPP2x*SBweight	-0.072**	-0.103	-0.044*	-0.089**	-0.059**	-0.181**	-0.027	-0.122***	-0.052*	-0.145*	-0.016	-0.090*	-0.023	-0.052	0.007	-0.042	-0.002	-0.018	0.022	-0.012
	(0.028)	(0.064)	(0.023)	(0.044)	(0.029)	(0.071)	(0.020)	(0.044)	(0.031)	(0.081)	(0.020)	(0.050)	(0.034)	(0.090)	(0.023)	(0.055)	(0.034)	(0.089)	(0.024)	(0.053)

Note: Robust standard errors are in parentheses. Asterisks designate statistical significance: ***—at the 1% level; **—at the 5% level; *—at the 10% level. Levels of banking and demographic characteristics are omitted for brevity.