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Allen N. Berger , Mustafa U. Karakaplan , Raluca A. Roman

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Whose Bailout Is It Anyway?
The Roles of Politics in PPP Bailouts of Small Businesses vs. Banks[§]

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Allen N. Berger
University of South Carolina,
Center for Financial Institutions at
Darla Moore School of Business,
Wharton Financial Institutions Center,
European Banking Center
aberger@moore.sc.edu

Mustafa U. Karakaplan
University of South Carolina,
Darla Moore School of Business
mustafa.karakaplan@moore.sc.edu

Stanford University
karakaplan@stanford.edu

Raluca A. Roman
Federal Reserve Bank of Philadelphia
raluca.roman@phil.frb.org

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Abstract

We address whether politics played important roles in allocating Paycheck Protection Program (PPP) bailout funds, and whether PPP allocations effectively bailed out small businesses and/or banks. Our econometric evidence suggests that politicians/other government agents at *national* and *local* levels effectively steered PPP funds toward small businesses and banks based on their locations to try to influence election outcomes. We also uncover evidence that some PPP funds were effectively allocated by lobbying efforts of certain banks. Findings are confirmed by a novel mediation analysis and numerous robustness checks. We also find banks profited from PPP through multiple channels, adding to extant findings, and suggesting that PPP may have effectively bailed out banks as well as small businesses, but through different political influences.

JEL Classification Codes: G01, G21, G28, D72

Keywords: politics, political influences, political economy, mediation analysis, bailouts, PPP, small businesses, banks, bank profitability, COVID-19 crisis.

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1. Introduction

The Paycheck Protection Program (PPP) is one of the largest U.S. government business bailouts of all time, distributing more than one half-trillion dollars in forgivable loans to five million+ small businesses during COVID-19. Banks issued over 90% of the PPP loans, were paid for distributing them, and gained access to government-supplied liquidity when needed, suggesting significant opportunities for banks to benefit as well.

We address two key questions noted in our title. First, using several dimensions of political influence, we investigate whether politics played important roles in effectively allocating Paycheck Protection Program (PPP) bailout funds to small businesses and/or banks. We find clear econometric evidence consistent with: a) *national* political influences via politicians and/or other government agents effectively helped steer more PPP funds toward banks, but not significantly toward small businesses, in county locations that may be particularly helpful in national election outcomes to support the party in power; b) *local* political influences via politicians/other government agents were able to effectively help guide relatively more funds toward small businesses, but not significantly toward banks, in ways that may help with reelections of congresspersons on a powerful committee. In addition, we find evidence that some banks, but not small businesses, effectively helped spur PPP funds their way through political lobbying.

Second, we address whether the PPP fund allocations substantially benefited or bailed out small businesses versus banks. The extant literature suggests sizable benefits for small business PPP recipients, with more limited evidence of bank benefits. We confirm and expand on the bank PPP evidence by analyzing their associated profitability gains from PPP and the channels behind these gains. We find that banks significantly profited through multiple channels. While it is not possible to directly compare small businesses and bank benefits due to different effects, the combined research evidence from this paper and extant literature strongly suggests that PPP may have effectively bailed out *both* small businesses and banks.

Our tests of the first question about political roles combine PPP loan data from the Small Business Administration (SBA) that administered the program, voting patterns captured by the Partisan Voter Index (PVI) in the Cook Political Report, information on representatives and lobbying from House and Senate websites, and other data on banks and counties to run the tests.

To clarify the framework for these tests, for *national* political influences, we consider first politicians/other government agents at the national level influencing allocation of PPP funds to small businesses, temporarily setting aside other agents. Given that the President was Republican during the PPP rollout in 2020, national government agents may try to steer more PPP funds to small businesses in part to increase the likelihood of national Republican wins in the 2020 elections – presidency, congressional majorities, and so forth. This may involve guiding funds toward small businesses based on the voting patterns in their locations. The national government agents may help allocate more PPP funds to small businesses in locations with voters near the center of the PVI to influence swing voters to the Republican side in the election. They may also help distribute more funds to firms in right-leaning locations to energize Republican base voters and/or campaigners, but not to left-leaning locations where more Democratic base voters reside.

We test these predictions in a log-odds model of the likelihood that a small business in a county obtains a PPP loan. As shown in Table 1, we construct *SmallBusCenter*, *SmallBusRight*, and *SmallBusLeft* variables to measure each small business' county *PVI* closeness to the center, right, and left of the political spectrum to test our predictions for influencing swing voters and energizing the Republican base. Consistency or non-consistency of the data with the predicted coefficients would be evidence for or against our predictions.

Analogous predictions/tests apply when we consider national government agents influencing the allocation of funds through banks using *BankCenter*, *BankRight*, and *BankLeft* based on bank headquarters locations. National government agents may help steer more PPP funds to center and right-leaning bank locations as well as or instead of center and right-leaning small business locations.

We specify both sets of variables in regressions to compare them and mitigate omitted-variable bias.

For *local* political influences, we consider U.S. House Representatives on an influential committee and their staffs as the local government agents that also have the potential to influence the distribution of PPP funds. Congresspersons may help small businesses or banks in their districts as a constituent service to win votes from locals of both parties for reelection. We test these predictions using coefficients on *SmallBusHSBComMem* and *BankHSBComMem*, reflecting membership on the House Small Business Committee known to influence PPP allocations (Table 1).

Small business and bank private-sector agents involved in PPP likely most often passively absorb the government largess and do not exercise connections to national or local government agents. The costs of lobbying or exercising other connections with government agents may often outweigh the PPP benefits. Nonetheless, significant minorities of small businesses and/or banks may find it worthwhile to use connections with national or local government agents. For data availability reasons, the only connections we evaluate are small business and bank lobbying, which requires elaborate matching efforts.[1] We test these in a separate model with lobbying variables – *LobbyBusCenter*, *LobbyBusRight, LobbyBusLeft*, *LobbyBankCenter, LobbyBankRight*, and *LobbyBankLeft* described in Table 1. Since lobbying data is only available for Congress at the national level, we again predict that any significant lobbying effects on PPP funds distribution would be most effective for the center and right-leaning political influences.

We draw conclusions for the first question about political roles in distributing PPP loans from the coefficients on these variables in the log-odds models as follows. First, we find relatively large positive and significant coefficients on *BankCenter* and *BankRight*, and relatively small and insignificant coefficients on *BankLeft, SmallBusCenter*, *SmallBusRight*, and *SmallBusLeft* when all are in the same regression. These results suggest national political influences significantly helped

[1] We use machine learning techniques to build the additional dataset of lobbying by both small businesses and banks matched to their locations and voting patterns in their counties.

allocate more PPP funds toward banks, but not small businesses. Analogously, our findings that local political influences significantly helped guide relatively more funds toward small businesses, but not banks, is based on a relatively large positive and significant coefficient on *SmallBusHSBComMem* and a relatively small and insignificant coefficient on *BankHSBComMem*. Our additional results of successful political lobbying by some of the banks, but not small businesses, are derived from large positive and significant coefficients on *LobbyBankCenter* and *LobbyBankRight*, and small and insignificant coefficients on *LobbyBankLeft, LobbyBusCenter*, *LobbyBusRight,* and *LobbyBusLeft*.

These main findings hold in many robustness tests, and are confirmed in robustness checks using data exclusions, alternative specifications, and heterogeneity across counties. Our findings are also robust to controlling for a county's rural/metropolitan status and examining heterogeneity across county, bank sizes and political extremes. We additionally flood the specifications with additional county controls.[2] We also find that variance inflation factors (VIFs) of the political influence variables and our full set of model variables are low, indicating correlations are modest and multicollinearity effects on standard errors are not concerning.

We also bolster our main findings by conducting a novel mediation analysis to understand better the economic magnitudes of the direct non-mediated effects and indirect mediated effects of our political influence variables on PPP fund allocations to small businesses and banks. The mediation analysis overwhelmingly supports our main results, and strongly suggests that bank direct political influences outweigh those of the small businesses in allocating PPP funds.

We acknowledge imprecision in capturing political influences due to data limitations. Our aggregation at the county level undoubtedly obscures heterogeneity and misses variations in political, economic, and financial factors within these jurisdictions (e.g., Gethin, Martínez-Toledano, and

[2] We also investigate political influences separately for the first and second waves of PPP funding – prior to April 17, 2020, and after April 26, 2020. We find that national political influences are stronger in the first wave, and the local influences are significant only in the first wave. These additional findings are consistent with expectations. PPP funds were in excess demand in the first wave and ran out in 13 days, while demand was more moderate in the second wave.

Piketty, 2022). Similarly, the distinctions between the political influences of government agents and those of small businesses and banks are likely not as cleanly separated as our assumptions may imply.

Finally, using both OLS and instrumental variable (IV) techniques, we analyze whether banks significantly benefited from PPP or were bailed out by the program. Our bank profitability analysis suggests that PPP participation boosted quarterly returns on assets and equity quite dramatically. Analyzing individual subcomponents of bank net income, we find that PPP bank participation increased their net interest income and decreased taxes paid, contributing to higher bank profitability. These are partially counteracted by increases in loan loss provisions which may reflect the narrower fiscal space due to PPP, and some decreases in gains from trading securities and net noninterest income. We additionally find strong support for channels of bank profitability through increased non-PPP commercial lending and competitive advantages that flow in part from this extra lending.

Our research adds to several strands of literature. Most closely related to our paper, two papers also investigate PPP and small business political influences. Duchin and Hackney (2021) and Igan, Lambert, and Mishra (2021) find that political influences increase the likelihood and size of PPP loans for small businesses, respectively. We complement and extend their findings by providing a more holistic picture of the role of politics in PPP bailouts. We specifically introduce political influences for steering funds toward banks as well as toward small businesses; include local political influences in addition to national politics; and include bank connections through lobbying as well as small businesses. Our specifications of bank as well as small business variables in the regressions also aid in comparison and mitigating omitted-variable bias. The mediation analysis of direct and indirect effects of political influences helps clarify the findings. Our second question findings that PPP bailed out banks through higher profitability via multiple channels also confirms the importance of including banks in the research evidence on political influences.

We also extend the existing literature on political influences in corporate finance more to include small businesses and banks that are often excluded from such analyses due to privately- held nd regulated status, respectively. Corporate findings suggest that political influences can be value-enhancing via preferential access to finance, favorable trade and tax benefits, government contracts, fewer regulations, and/or positive real economic outcomes (e.g., Fisman, 2001; Johnson and Mitton, 2003; Bertrand, Kramarz, Schoar, and Thesmar, 2004, 2018; Faccio, 2006; Leuz and Oberholzer-Gee, 2006; Classens, Feijen, and Laeven, 2008; Goldman, Rocholl, and So, 2013; Brown and Huang, 2020; Chu and Zhang, 2022). Others find value-destroying effects by exacerbating agency problems within the corporations, aiding managers that pursue personal objectives, and often find less favorable valuation outcomes (e.g., Aggarwal, Meschke, and Wang, 2012; Lee, Lee, and Nagarajan, 2014; Akey, Dobridge, Heimer, and Lewellen, 2018; Bertrand, Kramarz, Schoar, and Thesmar, 2018). Similar to our main analysis, some find political influences can significantly increase the likelihood of receiving corporate bailouts with both positive and negative valuation effects (e.g., Faccio, Masulis, and McConnell, 2006; Adelino, and Dinc, 2014).

For brevity's sake, we omit details but note that our findings are also inspired by and add to existing literatures on political influences in past bank bailouts, such as findings on TARP bank bailouts during the GFC (e.g., Duchin and Sosyura, 2012, 2014; Berger and Roman, 2015, 2017; Chavaz and Rose, 2019), and research on other aspects of PPP (e.g., Balyuk, Prabhala, and Puri, 2021; Erel and Liebersohn, 2022; Granja, Makridis, Yannelis, and Zwick, 2022; Griffin, Kruger, and Mahajan, 2023).

The remainder of the paper is organized as follows. Section 2 discusses our dataset and variables. Section 3 presents the econometric model and results for our analysis of political influences in PPP bailouts for small businesses and banks. Section 4 gives evidence on the direct mechanisms through which the political influences alter the distribution of PPP loans that provide additional support to our main results. Section 5 shows our investigation of the performance impacts of PPP on banks in terms of profitability, as well as the non-PPP lending and competitive advantage channels. Section 6 concludes, giving policy implications and future research suggestions.

2. Data and Variables

We conduct county-level analyses for the effects of political influences on the likelihood of PPP loans and bank-level analyses of the performance effects of banks making these loans. Many of the required variables – including the dependent variable for PPP loan likelihood – are available only at the county level.

We collect data from multiple sources. For the analyses at the county level, we start with the loan-level PPP data from the Small Business Administration's (SBA) website.[3] This dataset includes information almost all 5.2 million PPP loans from April to August 2020 and details about borrowers, lenders, and amounts. About 94% of these loans were made by banks for which we have additional information, and we focus on these loans for our analyses of small business versus bank bailouts.

We calculate the proportion of small businesses receiving PPP loans in a county using SBA PPP loan data. We convert the data to the county level using ZIP codes in the SBA data using the database of the U.S. Department of Housing and Urban Development's (HUD) Office of Policy Development and Research, with the Geocorr 2018 engine of the Missouri Census Data Center as a supplementary source to fill data gaps. In this conversion, when a one-to-one match is not possible, we weight the observations with the corresponding local population. We collect the number of small businesses in a county from the County Business Patterns of the US Census Bureau and calculate P as the number of PPP loans divided by the number of small businesses in that county.[4] We use the log-odds ratio $ln(P/(1-P))$ as our dependent variable for reasons discussed in Section 3. In Table 1, the mean of P is 0.707 with a standard deviation of 0.192, consistent with the widespread uptake of PPP.

Internet Appendix Figure IA.1 presents the geographical distribution of the small businesses

[3] https://www.sba.gov/funding-programs/loans/covid-19-relief-options/paycheck-protection-program/ppp-data

[4] We focus on the likelihood of a small business receiving a PPP forgivable loan, rather than the amounts of the loans. The amounts are formulaic and based on the payroll of the small business, and therefore are less subject to political influences.

in a county with respect to county population and *ln(P/(1−P))* in Panels A and B. Looking at Panel A, the number of small businesses per capita is mostly concentrated in the Western states of the Midwest, most of the states of the Great Plains, and the Northern states in proximity of the Rocky Mountains. Panel B shows a similar pattern for *ln(P/(1−P))*, which is the highest in the counties in the Great Plains.

We obtain the Partisan Voting Index (PVI) data from the Cook Political Report of 2012 and 2016. The PVI identifies the political leaning of a congressional district from the prior two presidential election results, ranging from up to 50 points Democratic and 50 points Republican. We convert this to an index from −50 to +50, where negative and positive values indicate strengths of Democratic and Republican support, respectively. The median district has a value of about 10, so we consider 10 as our center from which we measure closeness to the middle of the political spectrum for calculating our partisan political influences variables. We convert the data from congressional district to the county level as discussed above before creating our variables, again using the HUD and Geocorr databases. *SmallBusCenter*, *SmallBusRight*, and *SmallBusLeft* measure the closeness of the small businesses' county's *PVI* to the center for ranges of *PVI* in the middle, right, and left of the distribution, respectively, as shown in Table 1. We similarly create *BankCenter*, *BankRight*, and *BankLeft* based on the location of the lending banks' headquarters.

Figure 1 Panels A1 and A2 present the geographic distribution of the *PVI* based on the small businesses' counties and banks' counties, respectively. The right-leaning counties are mostly concentrated in the Great Plains, Texas, Southern states of the Midwest, and the Deep South. The left-leaning counties, on the other hand, are mostly concentrated in the East and West Coasts, Arizona, New Mexico, Colorado, and Northern states of the Midwest. The battleground and right-leaning counties in Panels A1 and A2 appear to overlap with the counties that have the largest *ln(P/(1−P))* in Internet Appendix Figure IA.1 Panel B, suggestive of political influences.

Our local political influences variables are based on the list of House Small Business Committee members from the House Small Business Committee's website. We first construct a dummy variable, *HSBComMem*, that takes the value of 1 if a congressional district is represented by a House member who served on the House Small Business Committee. We then form our two variables employed in the regressions, *SmallBusHSBComMem* and *BankHSBComMem*, based on this dummy variable in the small businesses' county and the banks' county, respectively.

The geographical distributions of *SmallBusHSBComMem* and *BankSBComMem* are presented in Figure 1 Panels B1 and B2. Counties in some states, such as Maine, Florida, Minnesota, Iowa, Oklahoma, Louisiana, Nevada, Utah, Idaho and Washington generally have the highest committee membership values. The counties in the Great Plains have the lowest committee membership values, except for those in Oklahoma.

For county controls, we collect 2019 data for rural/metropolitan status of a county (*MSA*), the percentage of low- and moderate-income population in a county (*%LMI*), education attainment (*% High Education*), and proportion of minority population (*% Minority*) from the U.S. Census American Community Surveys. Additionally, we gather the county unemployment rate (*Unemployment Rate*) from the U.S. Bureau of Labor Statistics (BLS), and the county house price index (*HPI House Index*) data from the Federal Housing Financing Agency (FHFA). Table 1 and Internet Appendix Table IA.1 present the brief definitions and summary statistics of these county-level control variables for the 3,138 counties in our sample.

Table 1 also shows variables collected from various sources on political lobbying by nonbank businesses in the counties of the PPP loan recipients and by banks in the headquarters counties of the banks that distributed the PPP loans. These variables are employed to test whether lobbying was the direct mechanism used by banks to exploit their political connections in influencing the distribution of PPP funds. These variables are discussed in Section 4.

For our bank-level analyses of bank performance, we obtain bank data from the quarterly

Call Reports for the period between 2019:Q1 and 2020:Q4 from the Federal Financial Institutions Examination Council (FFIEC) Central Data Repository and the Federal Reserve Bank of Chicago. Using these data as well as the FDIC Summary of Deposits (SoD) data from the Federal Deposit Insurance Corporation (FDIC), we create a set of dependent variables for bank performance. Our key measures of bank performance are profitability, *ROA* and *ROE,* the ratios of net income to gross total assets (*GTA*[5]) and equity, respectively. We also conduct a profitability decomposition analysis, in which we decompose bank net income into its various subcomponents, all scaled by GTA. For investigating the channels behind the bank profitability, we include commercial and industrial loans (*C&I Loans*), the ratio of C&I loans (excluding PPP loans) to *GTA* and commercial real estate loans (*CRE Loans*), the ratio of CRE loans to *GTA*. We also conduct additional tests of bank competitive advantages that may largely reflect this extra lending (see Internet Appendix, Table IA.4).[6]

The key right-hand-side variable (*BankPPPIntensity*) in our bank-level models is the number of PPP loans made by a bank in a quarter divided by the number of small businesses in that bank's county, normalized to be within the [0,1] interval. We merge the SBA loan-level PPP data with the Call Report bank-level data based on the PPP lender name and location to create this variable. We verify the match by checking the total outstanding balance of PPP loans of an institution in the two datasets.

For bank characteristics controls, we include proxies formed using Call Report data for CAMELS, six bank conditions of concern to bank supervisors. CAMELS proxies include: *Capital Adequacy*, the bank equity capital to *GTA*, *Asset Quality,* the ratio of nonperforming loans to *GTA*, *Management Quality*, the overhead costs ratio, determined as bank total interest and non-interest expenses to *GTA*, *Earnings*, annualized return on assets, *Liquidity*, the ratio of bank liquid assets over

[5] Gross total assets (*GTA*) adds back to Call Report total assets the allowance for loan and lease losses and the allocated transfer risk reserve. These reserves are held for potential credit losses and must be financed and so are part of bank size.
[6] As shown, most of the performance dependent variables are ratios to *GTA* or equity. In these cases, we lag the denominators because we are interested in the effects on bank involvement in PPP on the numerators only.

GTA, and *Sensitivity to Market Risk*, the absolute difference between short and long-term liabilities divided by *GTA*. We also include *Bank Size*, the natural logarithm of *GTA*, and a market concentration measure, *HHI*, the Herfindahl-Hirschman Index of bank deposits in their counties.

3. Regression Analyses of the Effects of Political Influences on the Likelihood of PPP Bailouts

We next present our econometric methodology and results for the likelihood that a small business in a county receives a forgivable PPP loan as a function of the national and local political influences of the small businesses and the banks, as well as county control variables.

3.1. Methodology

We employ the following log-odds model for each county:

$$\begin{aligned}\ln(P/(1-P)) = \alpha + \beta \cdot SmallBusPolInfl_{PRE} + \delta \cdot BankPolInfl_{PRE} \\ + \theta \cdot CountyControls_{PRE} + \varepsilon.\end{aligned} \tag{1}$$

The log-odds dependent variable $\ln(P/(1-P))$ groups the data from the small businesses in the county based on an underlying model of choices made by the small businesses, the banks, and the SBA, all of which must approve the loan. The log-odds formulation has the favorable property that the predicted probabilities always lie in the (0,1) interval. $SmallBusPolInfl_{PRE}$ and $BankPolInfl_{PRE}$ denote the key independent variable and correspond to the four different political influence variables (three national and one local) for influencing funds toward small business locations (*SmallBusCenter*, *SmallBusRight*, *SmallBusLeft*, and *SmallBusHSBComMem*) and bank locations (*BankCenter*, *BankRight*, *BankLeft,* and *BankHSBComMem*), respectively. The political influence variables preexist the PPP program for exogeneity reasons. National political influences are based on the 2012 and 2016 presidential elections, while the local influences employ 2019 congressional representation. County controls measured as of 2019 are *MSA*, *Unemployment Rate*, *% High Education*; *HPI House Index*; *% LMI*; and *% Minority*.

3.2. Main Results for the Roles of Political Influences in PPP Bailouts

Table 2 shows the main results. Columns (1) and (2) include only the political influences related to the locations of the small businesses and control variables. Viewed by themselves, these results might appear to suggest that national political influences of the small businesses are effective in increasing the likelihood of PPP bailouts. Both *SmallBusCenter* and *SmallBusRight* have positive statistically significant coefficients, while *SmallBusLeft* does not. These findings support the narrative that national political influences helped guide funds toward small businesses in counties that could help Republicans in the 2020 elections. Sending more government funds to center counties could help sway more marginal voters to the Republican side, and more funds to right-leaning counties could energize the Republican base, while funds to left-leaning counties would not help elect Republicans.

Columns (3) and (4) show the same specification except that they replace the small business locations with those of the bank – i.e., *BankCenter*, *BankRight*, and *BankLeft* based on bank headquarters county. The coefficients have slightly larger magnitudes and statistical significance.

Column (5) includes the national political influences of both the small businesses and the banks. The *BankCenter* and *BankRight* coefficients are positive, highly statistically significant, and in the expected directions, while the corresponding small business coefficients are small in magnitude, statistically insignificant, and of inconsistent signs. Thus, the data suggests that national political influences significantly helped allocate more PPP funds toward banks, but not toward small businesses.

Column (6) is our full specification. We add the local political influences for small businesses and banks, *SmallBusHSBComMem* and *BankHSBComMem*. The coefficient is positive and highly significant for the small business locations and not the banks', and the national political influences results are not materially affected. These findings are consistent with the narrative that local representatives would work to get more funds for the small businesses rather than the banks in their communities to increase their reelection chances. Robustness checks show that these effects are almost identical for Republican and Democratic representatives, consistent with the nonpartisan nature of local political influences (see Internet Appendix, Table IA.2, Column (7)).

Our findings are also economically significant. Additional calculations suggest that increasing *BankCenter* from 0 to 1 raises the predicted value of *P* by 4.8 percentage points, evaluated at the means of other regressors.[7] That is, a given small business would have almost a 5 percentage point greater likelihood of receiving a PPP loan if its bank is located in a county with voters at the median of the political spectrum as opposed to a bank in a county at the threshold of the center range. Similarly, increasing *BankRight* from 0 to 1, i.e., changing from a bank in a location on the far right of the spectrum to one closest to the center yields a predicted increase in *P* of 5.4 percentage points. Finally, a small business in a county represented on the House Small Business Committee has a predicted 6.2 percentage point higher likelihood of a PPP loan than one with no such representation.

We use variance inflation factor (VIF) in our full specification as a general diagnostic measure of potential multicollinearity. As a rule of thumb, a VIF above 10 would be an indication of high correlation and a concern about multicollinearity. In our full model, the VIFs of the political variables are within the range of [1.71, 2.77] and the mean VIF of the model is 2.31, indicating only modest correlations and no significant concerns about multicollinearity effects on standard errors.

We briefly note our findings for the control variables, limiting attention to those for which the coefficients are statistically significant. We focus on Column (6), but most of the control variable results are consistent across columns. The coefficients on *Unemployment Rate*, *% High Education*, and *% LMI* are all statistically significant and consistent with the theme that PPP funds were allocated more to areas that needed assistance the least, consistent with some of the PPP literature discussed in Section 2. That is, small businesses in counties with lower unemployment, higher education, and fewer residents of low and moderate income were more likely to receive PPP bailouts

[7] If the predicted value of $\ln(P/(1-P)) = X$, the predicted value of $P = e^X/(1+e^X)$.

for various reasons that may run counter to the social goals of the program.

3.3. Robustness Checks for the Roles of Political Influences in PPP Bailouts

We test the robustness of our main results to several alternative explanations in Internet Appendix Table IA.2 using our full specification in Column (6) of Table 2. In Appendix Table IA.2 Panel A Column (1), we exclude New York State counties, given that New York City is the nation's financial center that is known to have strong ties to Congress and banking regulators (e.g., Duchin and Sosyura, 2012). Columns (2), (3), and (4) exclude the top 10% of counties in terms of population in 2019, the bottom 10%, and both, respectively, to ensure that our findings are not driven by particularly large or small counties. In Column (5), we add regional fixed effects (Northeast, South, Midwest, and West) to rule out that geography, which is correlated with political parties, explains our results. In Column (6), we introduce additional controls for COVID-19 crisis severity using both % COVID-19 Cases/100K Population and % COVID-19 vulnerable industries in the county, and as well as a control for county population. These controls help address that the counties more intensely affected by the COVID-19 crisis could have demanded more PPP loans and that the degree to which US citizens perceived the crisis as a grave emergency may have varied along partisan lines (Bazzi, Fiszbein, and Gebresilasse, 2021).

Across all six regressions, *BankCenter*, *BankRight*, and *SmallBusHSBComMem* are all positive, large, and statistically significant. We again also find that none of the other political influences is statistically significant. These results provide strong confirmation of our main conclusions and help rule out alternative spurious explanations of our findings.

In Column (7) of Panel A, we check if the effects of local congressional representation on the House Small Business Committee differs significantly for Republican and Democratic representatives. The results clearly suggest no significant differences by party, supporting our interpretation as seeking reelection votes from both voters of both parties.

In Panel B, Columns (1) and (2), we exclude the top 1% most Democratic and most

Republican counties and the top 5%, respectively, to verify that our main evidence is not an artifact of the inclusion of political strongholds. In Columns (3), (4), and (5), we exclude counties that have at least a bank with $100 billion, $50 billion, and $1 billion in GTA, respectively, to confirm that our findings would hold with the counties that have no large banks. With a similar reasoning, in Column (6), we exclude counties with banks owned by the stress-tested BHCs in 2020.[8] Finally, in Column (7), we include county-level weighted averages of bank capital adequacy, asset quality, management quality, earnings, liquidity, sensitivity to market risk, using the banks' proportions of deposits in different markets as weights, and county bank competition proxied by the HHI of bank deposits, to control for the county-level banking environment. The results in Table IA.2 Panel B are similar to those in Panel A, again supporting the robustness of our key findings.

3.4. Political Influence Results Segmented by PPP Waves

In Table 3, we analyze if our political influence results differ between the first two PPP waves. The initial wave of PPP ended in 13 days on April 17, 2020, due to the depletion of the $349 billion originally allocated to PPP. The PPP program resumed after April 26, 2020, with an additional $320 billion in funds that lasted until August 8, 2020. Prior research suggests that the initial wave of PPP was oversubscribed and led to public uproar about its fair implementation due to credit rationing, suggesting that political influences may be more important in the first wave.

In Column (1), we analyze the data from the initial wave of PPP (before April 17), and find that *BankCenter*, *BankRight*, and *SmallBusHSBComMem* are statistically significant, positive, and even larger than for the full dataset, while other political variables remain insignificant. In Column (2), we analyze the data from the second wave of PPP (after April 26) and find that *BankCenter* and *BankRight* are still statistically significant and positive but not as large as in Column (1).

[8] The 33 participating BHCs in the 2020 CCAR exercise include: Ally Financial, American Express, Bank of America, Bank of New York Mellon, Barclays, BMO Financial, BNP Paribas, Capital One, Citigroup, Citizens Financial, Credit Suisse, Deutsche Bank USA, Discover, Fifth Third, Goldman Sachs, HSBC North America, Huntington Bancshares, JPMorgan Chase, KeyCorp, M&T Bank, Morgan Stanley, MUFG Americas, Northern Trust, PNC Financial, RBC US, Regions Financial, Santander Holdings, State Street, TD Group, Truist Financial, UBS Americas, U.S. Bancorp, and Wells Fargo. For details, see https://www.federalreserve.gov/publications/files/2020-dec-stress-test-results-20201218.pdf.

SmallBusHSBComMem is smaller and positive but not statistically significant. The other political variables again remain insignificant in the second PPP wave. Hence, these findings support our main evidence presented in Table 2 Column (6) and suggest political influences mattered in both waves, but they were more important in the initial PPP wave.

3.5. Political Influence Results Segmented by Bank and Small Business Size

Table 4 shows results segmented by the sizes of the banks and businesses in the counties. Table 4 Column (1) repeats our full-specification main results from Table 2, while Columns (2) and (3) show findings for smaller bank and larger bank counties – those with below and above median shares of banks with up to $100 million in GTA, respectively. Banks below this threshold are the smallest community banks that tend to specialize in relationship lending and have been shrinking in numbers considerably over time. Columns (4) and (5) display results for smaller business and larger business counties based on shares of small businesses below and above 500 employees based on County Business Patterns. This is based on the SBA definition of small businesses and its cutoff for PPP loans.

Starting with the results for small business locations, the coefficients on their national political influences are never large or statistically significant, and their local political influences are positive in all cases and statistically significant in all but one case. Thus, our findings for political influences to guide funds to small business locations remain intact and robust across counties dominated by smaller and larger banks as well as by smaller and larger businesses, except that the coefficients tend to be greater for counties dominated by smaller banks and smaller businesses.

For the banks, local political influences are never statistically significant, consistent with the main results. However, the results provide more moderate support for the national political influences. The *BankCenter* and *BankRight* coefficients are positive for all the county groups, but they are only consistently statistically significant for counties dominated by smaller banks and smaller businesses in Columns (2) and (4), respectively. For counties with larger banks and businesses in Columns (3) and (5), only one of four key national political influences coefficients are statistically significant. The results may reflect that the larger businesses with over 500 employees do not quality for PPP, and that these firms are more often served by larger banks. These findings suggest national political influences may not be successful for some banks in some counties.

3.6. Political Influence Results Segmented by Small Business Vulnerabilities

Table 5 presents findings for subsets of counties segmented by three characteristics that are related to the vulnerabilities of small businesses during the COVID-19 crisis: 1) those with low versus high proportion of Low- and Moderate-Income (LMI) census tracts in them based on median family income being less than 80% of the area median; 2) those with low versus high industry vulnerability to COVID-19 based on the Chmura Economics and Analytics proprietary model of industry job losses for 2-digit NAICS; and 3) low versus high COVID-19 cases per 100K population from the John Hopkins Coronavirus Center.

Again, starting with small business findings, national political influences continue to be statistically insignificant whenever the bank locations are included. Local influences are also positive in all cases and statistically significant in four instances. The magnitudes are greater for the subsamples of counties where the need is greatest for the PPP funds – lower income, more COVID-19-impacted industries, and more COVID-19 cases per capita. This suggests that the local influences shifting funds toward small business locations worked more where they were most needed.

The bank results in Table 6 again show their local political influences are never statistically significant, consistent with the main findings. For national political influences, the *BankCenter* coefficients are positive and significant for all the county groups, while the *BankRight* coefficients are all positive and statistically significant in four of six cases. These findings again suggest that national political influences are influential in many circumstances, but that closeness to the center of the political spectrum may work in more scenarios than being on the political right.

Overall, our investigation by county heterogeneity in Sections 3.5 and 3.6 is strongly consistent with our main conclusions – national political influences were effective in allocating more PPP funds toward banks but not toward small businesses, whereas local influences helped steer relatively more funds towards small businesses, but not toward banks. The findings also suggest that in some cases, the political influences are stronger or only strong in scenarios where this may be expected, such as counties where smaller banks and smaller businesses dominate, and in counties in which the PPP funds were more crucially needed.

3.7. Mediation Analysis

Because our main effects may operate through multiple political influences simultaneously, we would ideally want to estimate a model consistent with such complexities. Particularly, one concern may be that a proposed influence may be correlated with the real influence but not caused by the independent variable, which can lead to misspecification problems. Moreover, different theories may postulate different mediators as mechanisms, so including them all in a model simultaneously allows for formal statistical comparison of indirect effects representing different theoretical explanations.

To address these concerns and help gauge the economic magnitudes of the direct non-mediated effects and indirect mediated effects of political influences on PPP, we follow prior research (e.g., Preacher and Hayes, 2004; Malceniece, Malcenieks, and Putnin, 2019) and conduct a mediation analysis with the following structural equations model where *BankPolInfl* is the independent variable, *SmallBusPolInfl* the mediating variable, and *ln(P/(1 − P))* is the dependent variable:

$$\mathbf{1}\text{: } ln(P/(1-P)) = \alpha_1 + \delta \cdot BankPolInfl_{PRE} + \theta_1 \cdot CountyControls_{PRE} + \varepsilon.$$

$$\mathbf{2}\text{: } SmallBusPolInfl_{PRE} = \alpha_2 + \mu \cdot BankPolInfl_{PRE} + \varphi.$$

$$\mathbf{3}\text{: } ln(P/(1-P)) = \alpha_3 + \rho \cdot SmallBusPolInfl_{PRE} + \theta_3 \cdot CountyControls_{PRE} + \omega.$$

The first equation indicates the direct (non-mediated) effect (represented by coefficient estimates δ), whereas the second and third equations together represent the mediated effect (the magnitude of which is $\mu \times \rho$). Specifically, we denote δ_C, δ_R, and δ_L as the direct effects of the *BankCenter*, *BankRight*, and *BankLeft* on *ln(P/(1-P))*, respectively; while μ_C, μ_R, and μ_L are the effects of the *BankCenter*, *BankRight*, and *BankLeft on SmallBusCenter, SmallBusRight, and SmallBusLeft*, respectively; and ρ_C, ρ_R, and ρ_L are the direct effects of the *SmallBusCenter*, *SmallBusRight*, and *SmallBusLeft* on *ln(P/(1-P))*, respectively.

Our mediation analysis findings are summarized in Figure 2. We find that 72% of the total effect of *BankCenter* on *ln(P/(1-P))* is its direct effect, and 28% is mediated through *SmallBusCenter*. For *BankRight*, however, 99% of its total effect on *ln(P/(1-P))* is its direct effect, and only 1% is mediated through *SmallBusRight*. These results provide strong support to our main findings and that bank political influences have likely most important direct effects on PPP, while only a small percent is mediated through small business political influences. To test the degree to which the mediating variable explains the relationship between the independent and dependent variables, we follow Sobel (1982) and Preacher and Hayes (2004, 2008) and find that the Sobel statistics of mediation are 0.899 and 0.013, respectively. Hence, the mediated effects are not statistically significant.

4. Regression Analyses of the Effects of Political Connections of Small Businesses and Banks

This section provides evidence on political connections of small businesses and banks. As explained in the Introduction, most small business and bank PPP participants likely most often passively absorbed the government funds without exercising connections, given costs relative to benefits. We test whether some small businesses and/or banks may have effectively used connections with national government agents via lobbying.

The political science literature suggests that lobbying is the main direct method for U.S. companies to influence government and accounts for most of their political expenditures (e.g., Wright, 1990; Ansolabehere, de Figueiredo, Snyder, 2003; Adelino and Dinc, 2014). In the case of PPP, Igan, Lambert, and Mishra (2021) focus on the lobbying of the businesses and not the banks, and find that lobbying at the firm and industry levels is associated with larger dollar sizes for PPP loans.

We collect our own lobbying dataset that allows us to consider and compare the effects of lobbying by banks and businesses on the likelihood of PPP loans. Our econometric setup explained below mimics our analysis in Table 2 to determine if the incidence of the lobbying corresponds well with the incidence of national political influences.

The Lobbying Disclosure Act of 1995 and subsequent amendments require that those lobbying the federal government either by themselves or via other entities report their lobbying activities to the U.S. Senate Office of Public Records. We collect these lobbying data from both the U.S. Senate Lobbying Database and the LobbyView.com website (Kim, 2018). We then use machine learning to scrape additional information from YellowPages.com to identify addresses of the lobbying clients and determine which are nonbank businesses versus banks. We construct lobbying measures by nonbank businesses in the counties in which PPP loan recipients are located and bank lobbying in the headquarters counties of the banks that distributed the PPP funds to construct the exogenous variables for this analysis.

The econometric results are shown in Table 6. The regressions mimic those in Table 2 and use the same dependent variable $ln(P/(1-P))$, but replace the political influence variables there with lobbying intensities for the nonbank businesses and banks in counties that differ by their past voting patterns. Thus, *LobbyBusCenter* is the number of businesses that lobbied the federal government between 2016 and 2019 divided by the total number of businesses in center-leaning counties of the businesses that received PPP loans with PVI values within 10 points of the center. It is set to zero for right- and left-leaning counties further away from the center on the right and left. *LobbyBusRight,* and *LobbyBusLeft* are defined similarly for the other two sets of counties of these businesses. *LobbyBankCenter, LobbyBankRight,* and *LobbyBankLeft* are constructed analogously for counties of the banks that distributed the PPP loans. Table 1 and Internet Appendix Table IA.1 show definitions of these lobbying variables and their summary statistics, respectively. Control variables are identical to those in Table 2.

Our findings for the effects of lobbying in Table 6 closely match the patterns in Table 2, providing credible evidence that lobbying is the direct mechanism for these influences. Again, the center and right effects are positive and statistically significant for the businesses when the bank variables are excluded in Columns (1) and (2), and for the bank variables when the small business variables are excluded in Columns (3) and (4), and only the bank variables are significant when both are included in Columns (5) and (6). In Column (6), we continue to observe positive and significant effects of local influences for small businesses and not for the banks.

5. Regression Analyses of the Effects of PPP Bailouts on Bank Performance

This section provides methodology and results for the effects of banks' intensity of PPP participation on their performance. We focus on bank profitability and subcomponents. We also investigate two main channels through which the profitability may be achieved – additional lending above and beyond the PPP loans and greater competitive advantages in terms of market shares and market power relative to other banks with less involvement. In all cases, we show results for all banks, smaller banks, and larger banks, and for both OLS and instrumental variables (IV) estimations, using political influences as instruments for PPP participation based on our findings above.

5.1. Methodology

We estimate the following model for the quarterly performance of individual banks over the period 2019:Q1-2020:Q4:

$$Performance_{j,t} = \varphi_0 + \varphi_1 BankPPPIntensity_{j,t-1} + \varphi_2 BankControls_{j,t-1} + \varphi_3 BankFE_j + \varphi_4 YearQuarter_t + \varsigma_{j,t}. \tag{2}$$

The dependent variable is a bank performance variable for bank j in quarter t. For bank profitability, we include *ROA* and *ROE* (or their subcomponents). For bank lending performance, we include *C&I Loans* and *CRE Loans*. For bank competitive advantages in Internet Appendix Table IA.4, we use *Market Share Assets* and *Market Share Loans*, and for bank market power, we use the *Lerner Index*.

The key explanatory variable is *BankPPPIntensity*, a bank's PPP lending intensity. Bank controls include lagged values of variables commonly specified in the banking literature – proxies for bank regulatory CAMELS, *Bank Size*, and *HHI*. We include bank fixed effects to capture other unobservable differences among banks that remain invariant during our sample period and Year-Quarter fixed effects to absorb common temporal shocks.

For all the performance variables, we report results for all banks, smaller banks, and larger banks for both OLS and IV to help ensure robustness. Panels A in Tables 7 to 9 show the OLS results, and Panels B show the second-stage IV results using *BankCenter(bank)* as the instrument for *BankPPPIntensity*. As indicated in Table 1, *BankCenter(bank)* is the weighted average of *BankCenter* for the counties in which the bank has branches, and measures one dimension of the bank's national political influences. It is a valid instrument based on our results above that *BankCenter* significantly increases PPP participation. Our results are also robust when using *BankRight(bank)*, which is equally valid, but not shown for brevity. Appendix A shows the first stage regressions for both instruments, which have large t-statistics for the instruments and large F-values for the regressions.

5.2. Results for the Effects of PPP Bailouts on Profitability Performance

Table 7 gives performance results for bank profitability measured by *ROA* and *ROE*. Panel A reports OLS results, while Panel B reports the 2nd stage of the IV results. Across both the OLS and IV specifications, and for both *ROA* and *ROE,* we find that banks with more intensive PPP participation increased their profitability. *BankPPPIntensity* in the IV specifications are statistically significant even with respect to the tF-statistics à la Lee, McCrary, Moreira, and Porter (2022), and its coefficients are much larger in magnitude than those in OLS, consistent with strong local average treatment effects as discussed in Jiang (2017). Thus, banks with stronger political influences increase their profitability more, consistent with banks' motives to use their orientations to improve their performance. We also observe that the increases in profitability are much larger for smaller banks, consistent with prior findings in the PPP literature noted above. Thus, our profitability findings are consistent with banks' motives to profit from their PPP involvement, particularly for smaller banks.

The effects of *BankPPPIntensity* on bank profitability are also economically significant. Using the coefficients from the OLS estimations, we calculate the predicted values of quarterly *ROA* and *ROE* for *BankPPPIntensity* at both 0 and its national average of 0.052, holding all other regressors at their mean values. This exercise suggests that a bank with average PPP involvement would have higher predicted quarterly *ROA* and *ROE* by 25% and 39%, respectively, relative to a bank that did not participate in PPP. Analogous calculations for the IV estimates yield larger effects.

5.3. Results for the Effects of PPP Bailouts on Drivers of Bank Profitability Performance

We next analyze possible key drivers of the increase in the above documented bank profitability. In particular, increases in bank profitability may also stem from gains from trading securities and/or decreases in loan loss provisions in addition to other traditional drivers of profitability. First, banks' gains and losses from trading securities could have been affected given that the implementation of the PPP occurred around the same time that the Federal Reserve Bank announced additional government lending facilities and quantitative easing policies. Particularly, the Primary and Market Corporate Credit Facility (PMCCF) and the Secondary Market Corporate Credit Facility (SMCCF), both were introduced on March 23, 2020, to support credit to businesses particularly through bond issuances or purchases of existing corporate bonds (e.g., Cortes, Gao, Silva, and Song, 2022; Hartley, Rebucci, and Jiménez, 2021). These may have temporarily inflated security prices and enabled banks to achieve higher gains from securities transactions. Second, banks' loan loss provisions may also be affected as they typically reflect the fiscal conditions of the government, which indicate the strength of implicit guarantees and the credibility of fiscal multipliers (Silva, 2021). PPP could either increase or decrease loan loss provisions. On one hand, given PPP is primarily viewed as financial aid to small business borrowers, banks could lower the loan provisions to reflect lower perceptions of credit risk from PPP. But on the other hand, due to the massive fiscal costs associated with the PPP program, banks could increase their provisions to reflect the narrower fiscal space.

Given that net income, the numerator of *ROA* and *ROE* can be decomposed into *(net interest income + net non-interest income + gains and losses from securities trading - loan loss provisions - taxes)*, we conduct an additional analysis in which we consider each of these variables scaled by bank GTA as dependent variables. We report both the OLS and IV 2SLS results for all banks in Table 8 Panels A and B, while we report corresponding results for smaller and larger banks in the Internet Appendix Table IA.3. We find that banks with more intensive PPP participation significantly increased their net interest income and decreased taxes paid (PPP forgivable loans were not taxable with possible implications for both businesses and banks), both components contributed to higher bank profitability. These are counteracted partly by increases in loan loss provisions which may reflect the narrower fiscal space due to PPP, and some decreases in gains from trading securities and net noninterest income, the latter two however only being statistically significant in their IV specifications. Appendix Table IA.3 also shows that the smaller banks' effects are most pronounced.

5.4. Results for the Effects of PPP Bailouts on Bank Lending Performance

Table 9 reports the performance results for commercial and industrial loans exclusive of PPP loans (*C&I Loans*) and commercial real estate loans (*CRE Loans*), respectively, to see if additional lending is a channel for the increased profitability. Across all specifications, we find that banks with more intensive PPP participation increased non-PPP commercial lending. Again, the results are stronger for smaller banks and in the IV specifications. These findings support the lending channel for the observed boost in bank profitability.

Internet Appendix Table IA.4 shows results for bank competitive advantages proxied by market shares and market power, respectively. For *Market Share Assets* and *Market Share Loans* we treat counties as local banking markets and assume that bank assets and loans are geographically distributed across counties as are their deposits, for which we have complete location information from the FDIC Summary of Deposits.[9] Bank market power is proxied by the *Lerner Index*, price-cost margin divided by price, (*Price*-*MC*)/*Price*, details of which are shown in Internet Appendix, Additional Material. Consistent with the lending performance results, the coefficients on *BankPPPIntensity* are all positive and statistically significant, and greater in magnitude for IV than OLS, and for smaller banks than larger banks. The bank increased competitive advantages from PPP may largely reflect the increased lending documented above.

The findings throughout Section 5 are consistent with the narrative that banks are motivated to use their orientations to increase their PPP involvement in order to improve their performance.

6. Research and Policy Implications

Our empirical results of political influences on government funds and bailouts of the small businesses and banks are perhaps not that surprising. However, our finding that the political influences are so widespread is somewhat jarring. We find evidence of political influences of both politicians/other government agents and private-sector firms, both national and local politicians/other government agents, both small businesses and banks in the private sector, and both partisan and nonpartisan motives by the government agents, etc. It appears that very substantial efforts by many parties are invested in allocating government funds for reasons other than the intended purposes of the program.

[9] These assumptions are based on the "cluster" approach frequently employed in the banking literature (e.g., Berger and Hannan, 1989; Cyrnak and Hannan, 1999), This approach originated in the Supreme Court's 1963 Philadelphia National Bank decision, which found that banks produce a "cluster" of services that are traded in "local markets."

In terms of policy and research implications, it is difficult to objectively address the question of whether the political influences are reasonable prices to pay to have a policy program that the literature suggests was mostly successful in save small businesses, employees, and the economic and financial system. However, the implications for the importance of collecting more data and engaging in more research on political influences are clear, as are finding better policy solutions to target the funds and limit investments in divert the funds for alternative purposes.

Addressing this question in a future research agenda might require specifying a general equilibrium model of political economy and performance of a comprehensive welfare analysis. The results of such an exercise may depend on the balance of political power between the two political parties; the balance of influence between party leaders and rank-and-file local congressional representatives, and the lobbying and other connections of the small businesses versus the banks. As well, the outcomes may be very different if the Democrats versus Republicans have charge of the Presidency and Senate and/or House chambers.

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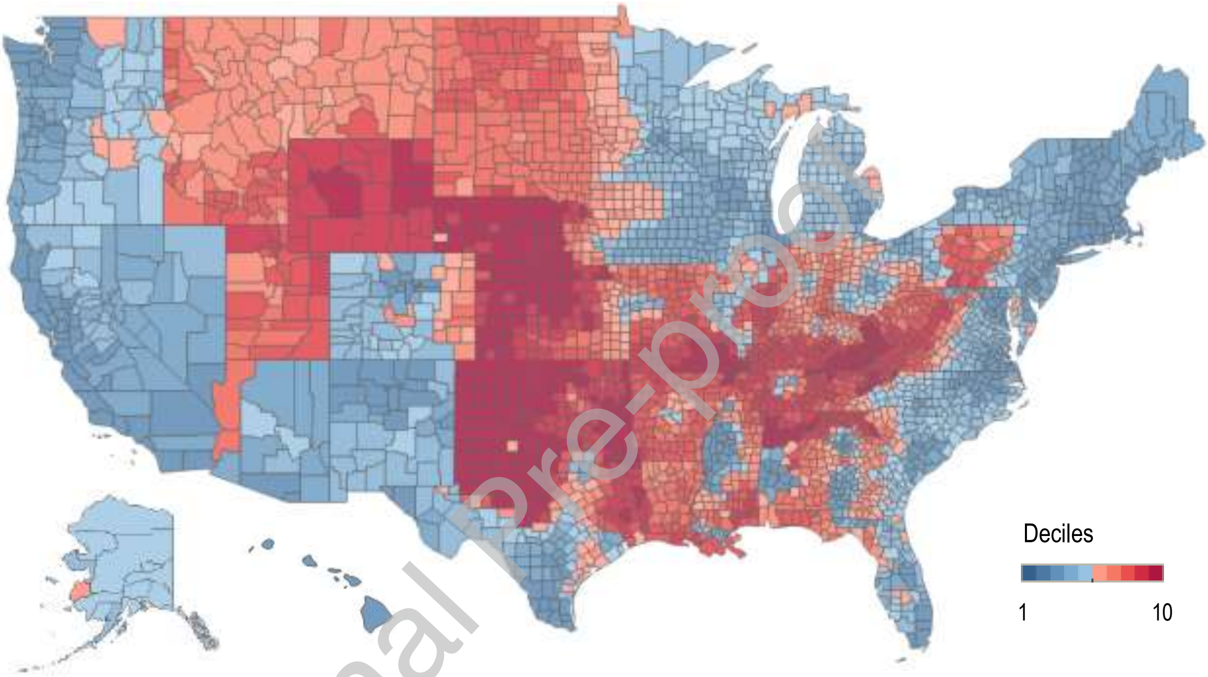
Figure 1: Heat Maps of
Political Influences for Small Businesses and Banks

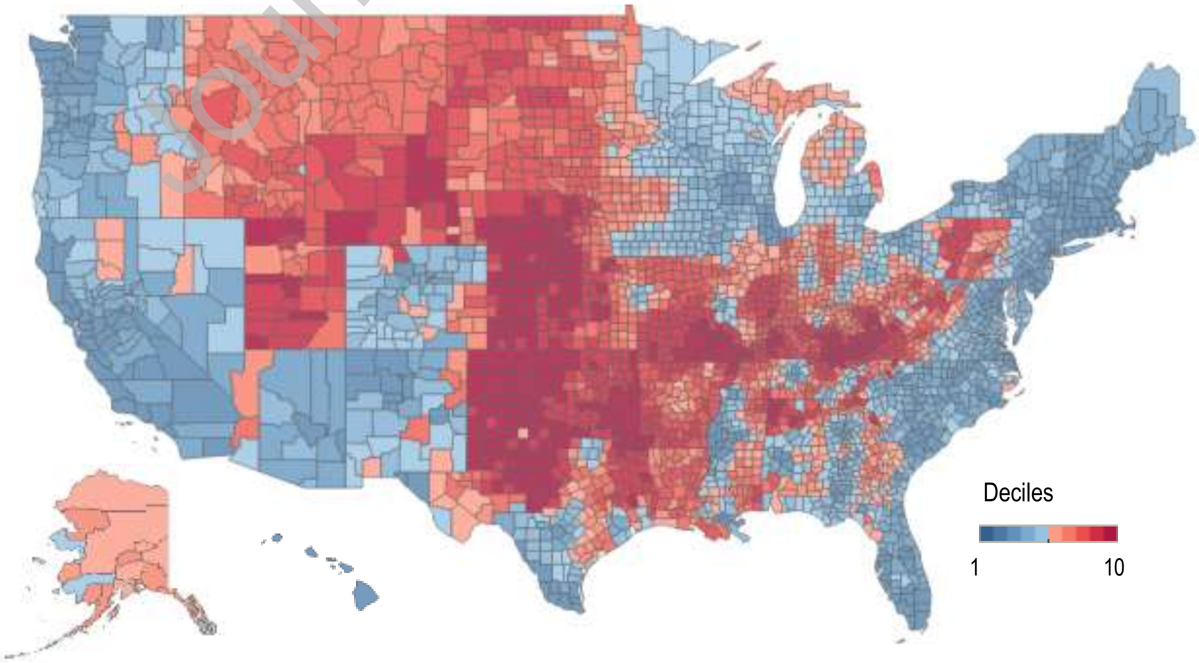
This figure presents the geographical distribution of national and local political influences for banks across counties in the U.S. The figures present ten categories which were obtained based on an equal deciles' methodology. In Panel A, we cover the distribution of national political influences, darker blue colors represent smaller *PVI* values while darker red colors represent larger *PVI* values for small businesses and banks, respectively. Finally in Panel B, covering the distribution of local political influences, darker brown colors represent larger values of *HSBComMem* for small businesses and banks, respectively.

Panel A: Partisan Voting Index (*PVI)*

Panel A1: *SmallBusPVI* (national political influences for small businesses)

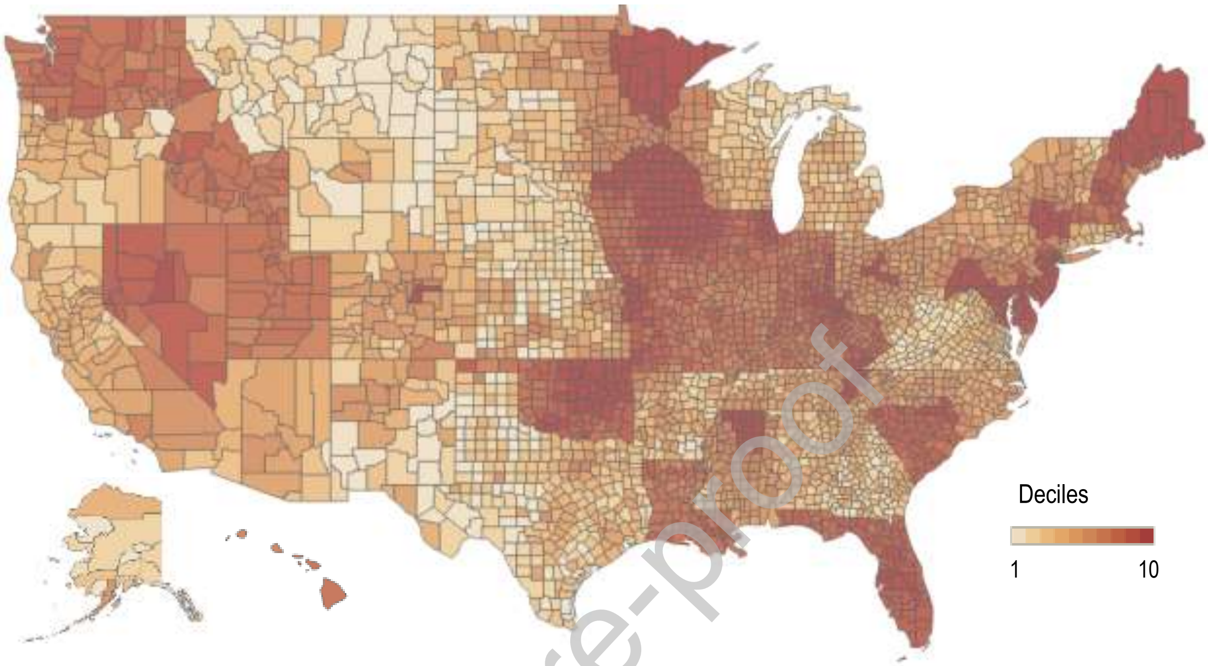


Panel A2: *BankPVI* (national political influences for banks)



Panel B: *HSBComMem*

Panel B1: *SmallBusHSBComMem* (local political influences for small businesses)



Panel B2: *BankHSBComMem* (local political influences for banks)

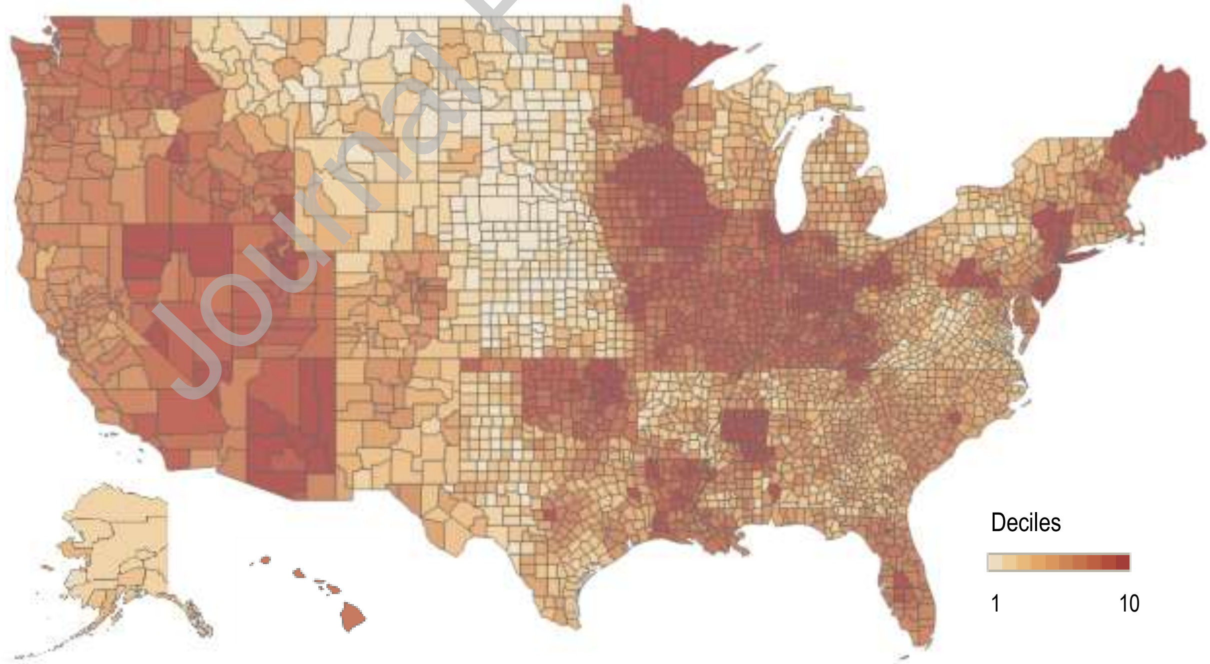


Figure 2: Direct and Mediated Effects of Bank Political Influences (*BankPolInfl*) on *ln(P/(1-P))*

This figure depicts the results from the mediation analysis of the *BankPolInfl* on the log-odds ratio. The estimates are derived from the following structural equations model:

$$ln(P/(1-P)) = \alpha_1 + \delta \cdot BankPolInfl_{PRE} + \theta_1 \cdot CountyControls_{PRE} + \varepsilon.$$
$$SmallBusPolCon_{PRE} = \alpha_2 + \mu \cdot BankPolInfl_{PRE} + \varphi.$$
$$ln(P/(1-P)) = \alpha_3 + \rho \cdot SmallBusPolInfl_{PRE} + \theta_3 \cdot CountyControls_{PRE} + \omega.$$

where δ_C, δ_R, and δ_L are the direct effects of the *BankCenter*, *BankRight*, and *BankLeft* on *ln(P/(1-P))*, respectively; μ_C, μ_R, and μ_L are the effects of the *BankCenter*, *BankRight*, and *BankLeft on SmallBusCenter, SmallBusRight, and SmallBusLeft*, respectively; and ρ_C, ρ_R, and ρ_L are the direct effects of the *SmallBusCenter*, *SmallBusRight*, and *SmallBusLeft* on *ln(P/(1-P))*, respectively. τ_C, τ_R, and τ_L are the total effects of the *BankCenter*, *BankRight*, and *BankLeft* on *ln(P/(1-P))*. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

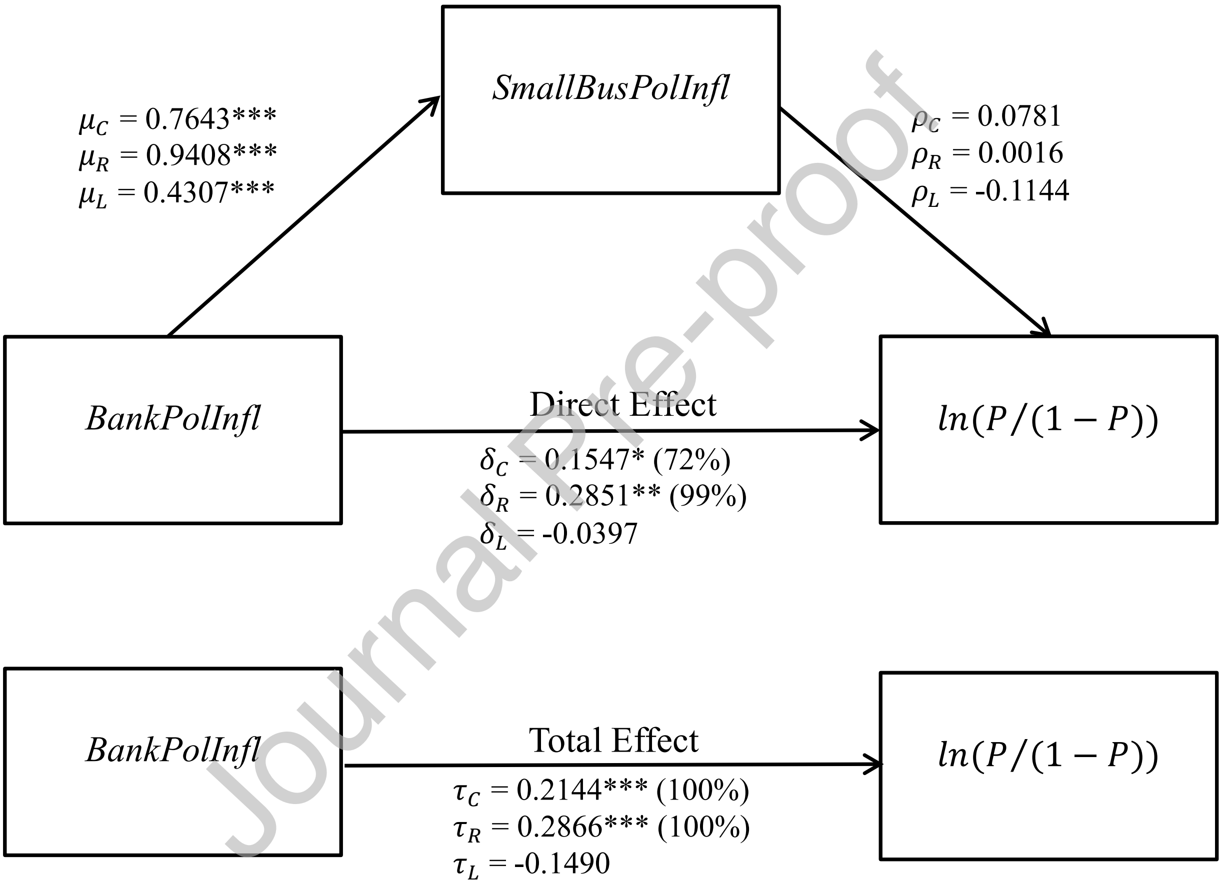


Table 1: Variable Definitions

This table provides the definitions and data sources of the variables used in our analyses.

Variable	Definition	Data Source
County-Level Variables		
P	Proportion of PPP loans in a county, number of PPP loans divided by the number of small businesses in a county. Not directly included in the regressions.	SBA, County Business Patterns
ln(P/(1-P))	The log-odds ratio of *P*.	SBA, County Business Patterns
PVI	Proxy for political influences, denoting the political leaning of a congressional district based on the 2012 and 2016 presidential election results, ranging from −50 to +50, where negative and positive values indicate strengths of Democratic and Republican support, respectively. The median district has a value of 10, so we consider 10 as our center from which we measure closeness to the middle of the political. We convert *PVI* from congressional district to the county level. Not directly included in the regressions.	Cook Political Report
SmallBusCenter	Proxy for political influences, denoting the closeness of the small businesses' county's *PVI* to the center for values within ±10 points around the center, normalized to be in the [0,1] interval.	Cook Political Report, SBA
SmallBusRight	Proxy for political influences, denoting the closeness of the small businesses' county's *PVI* to the center for values greater than 10 points above the center, normalized to be in the [0,1] interval.	Cook Political Report, SBA
SmallBusLeft	Proxy for political influences, denoting the closeness of the small businesses' county's *PVI* to the center for values smaller than 10 points below the center, normalized to be in the [0,1] interval.	Cook Political Report, SBA
BankCenter	Proxy for political influences, denoting the closeness of the banks' county's *PVI* to the center for values within ±10 points around the center, normalized to be in the [0,1] interval.	Cook Political Report, SoD
BankRight	Proxy for political influences, denoting the closeness of the banks' county's *PVI* to the center for values greater than 10 points above the center, normalized to be in the [0,1] interval.	Cook Political Report, SoD
BankLeft	Proxy for political influences, denoting the closeness of the banks' county's *PVI* to the center for values smaller than 10 points below the center, normalized to be in the [0,1] interval.	Cook Political Report, SoD
HSBComMem	Proxy for local political influences, takes the value of 1 if a congressional district is represented by a House member serving on the House Small Business Committee in 2019, and 0 otherwise.	House of Representatives website
SmallBusHSBComMem	Proxy for local political influences, takes the value of *HSBComMem* if there is exactly one congressional district in the small businesses' county in 2019, and equals the average of *HSBComMem* in the county otherwise.	House of Representatives website, Missouri Census Data Center, SBA
BankHSBComMem	Proxy for local political influences, takes the value of *HSBComMem* if there is exactly one congressional district in the banks' county in 2019, and equals the average of *HSBComMem* in the county otherwise.	House of Representatives website, Missouri Census Data Center, SoD
MSA	Takes the value of 1 when majority of census tracts (50% or more) in a county are in metropolitan areas in 2019, and 0 otherwise.	US Census American Community Surveys
Unemployment Rate	The unemployment rate in a county in 2019.	US Bureau of Labor Statistics
% High Education	The percentage of population with college degree or higher in the county in 2019.	US Census American Community Surveys
HPI House Index	FHFA house price index in a county in 2019.	FHFA
% LMI	The proportion of Low- and Moderate-Income census tracts in a county in 2019, where a census tract is defined as being LMI if its median family income is less than 80% of the area median family income.	US Census American Community Surveys
% Minority	The percent of population that is racial and ethnic minority in 2019.	US Census American Community Surveys
Variables for County Subsamples and Lobbying		
NY State	Takes the value of 1 if a county is in the state of New York, and 0 otherwise.	County Business Patterns
Top 10% Counties	Takes the value of 1 if a county is in top 10% largest counties based on county population in 2019, and 0 otherwise.	US Census
Bottom 10% Counties	Takes the value of 1 if a county is in bottom 10% largest counties based on county population in 2019, and 0 otherwise.	US Census
US Regions	Four regions of the US: Northeast, South, Midwest, and West.	US Census

Variable	Definition	Data Source
Variables for County Subsamples and Lobbying (cont.)		
% COVID-19 Cases/100KPop	COVID-19 cases per 100K population in a county.	John Hopkins Coronavirus Center
% COVID-19 Vuln. Industries	COVID-19 Economic Vulnerability Index for the counties in 2019.	Chmura Economics & Analytics, JobsEQ
ln(County Population)	Natural logarithm of county population in 2019.	US Census
CB Capital Adequacy	Weighted average of banks' *Capital Adequacy* (explained below) in a county, using the banks' proportions of deposits in different markets as weights.	Call Reports
CB Asset Quality	Weighted average of banks' *Asset Quality* (explained below) in a county, using the banks' proportions of deposits in different markets as weights.	Call Reports
CB Management Quality	Weighted average of banks' *Management Quality* (explained below) in a county, using the banks' proportions of deposits in different markets as weights.	Call Reports
CB Earnings	Weighted average of banks' *Earnings* (explained below) in a county, using the banks' proportions of deposits in different markets as weights.	Call Reports
CB Liquidity	Weighted average of banks' *Liquidity* (explained below) in a county, using the banks' proportions of deposits in different markets as weights.	Call Reports
CB Market Risk Sensitivity	Weighted average of banks' *Sensitivity to Market Risk* (explained below) in a county, using the banks' proportions of deposits in different markets as weights.	Call Reports
CB HHI	Banks' *HHI* of deposits (explained below) in a county.	SoD
Smaller Bank Counties	Counties below the median of smaller (< $100 Million Gross Total Assets (*GTA* explained below)) bank share.	Call Reports
Larger Bank Counties	Counties above the median of smaller (< $100 Million *GTA*) bank share.	Call Reports
Smaller Business Counties	Counties below the median of smaller (< 500 Employees) small business share.	County Business Pattern
Larger Business Counties	Counties above the median of smaller (< 500 Employees) small business share.	County Business Pattern
Low % LMI Counties	Counties below the median of the proportion of Low- and Moderate-Income (*LMI*) population in a county in 2019.	US Census American Community Surveys
High % LMI Counties	Counties above the median of *LMI*.	US Census American Community Surveys
Low % COVID-19 Affected Industries	Counties below the median of COVID-19 Economic Vulnerability Index by counties in 2019.	Chmura Economics & Analytics, JobsEQ
High % COVID-19 Affected Industries	Counties above the median of COVID-19 Economic Vulnerability Index by counties in 2019.	Chmura Economics & Analytics, JobsEQ
Low % COVID-19 Cases/Pop	Counties below the median of COVID-19 cases in a county per 100K population.	John Hopkins Coronavirus Center
High % COVID-19 Cases/Pop	Counties above the median of COVID-19 cases in a county per 100K population.	John Hopkins Coronavirus Center
LobbyBusCenter	Lobbying intensity of nonbank businesses in a center-leaning county of businesses that received PPP loans, calculated as the number of businesses in the county that lobbied between 2016 and 2019 divided by the total number of businesses in the county. A county is center-leaning if the county's *PVI* is within 10 points of the center. This variable is set to zero for right- and left-leaning counties further away from the center on the right and left.	US Senate Lobbying data, LobbyView website, Cook Political Report, SBA
LobbyBusRight	Lobbying intensity of nonbank businesses in a right-leaning county of businesses that received PPP loans, calculated as the number of businesses in the county that lobbied between 2016 and 2019 divided by the total number of businesses in the county. A county is right-leaning if the county's *PVI* is greater than 10 points above the center. This variable is set to zero for other counties.	US Senate Lobbying data, LobbyView website, Cook Political Report, SBA
LobbyBusLeft	Lobbying intensity of nonbank businesses in a left-leaning county of businesses that received PPP loans, calculated as the number of businesses in the county that lobbied between 2016 and 2019 divided by the total number of businesses in the county. A county is left-leaning if the county's *PVI* is smaller than 10 points below the center. This variable is set to zero for other counties.	US Senate Lobbying data, LobbyView website, Cook Political Report, SBA
LobbyBankCenter	Lobbying intensity of banks in a center-leaning county of banks that distributed PPP loans, calculated as the number of banks in the county that lobbied between 2016 and 2019 divided by the total number of banks in the county. A county is center-leaning if the county's *PVI* is within 10 points around the center. This variable is set to zero for right- and left-leaning counties further away from the center on the right and left.	US Senate Lobbying data, LobbyView website, Cook Political Report, SoD

Variable	Definition	Data Source

Variables for County Subsamples and Lobbying (cont.)		
LobbyBankRight	Lobbying intensity of banks in a right-leaning county of banks that distributed PPP loans, calculated as the number of banks in the county that lobbied between 2016 and 2019 divided by the total number of banks in the county. A county is right-leaning if the county's *PVI* is greater than 10 points above the center. This variable is set to zero for other counties.	US Senate Lobbying data, LobbyView website, Cook Political Report, SoD
LobbyBankLeft	Lobbying intensity of banks in a left-leaning county of banks that distributed PPP loans, calculated as the number of banks in the county that lobbied between 2016 and 2019 divided by the total number of banks in the county. A county is left-leaning if the county's *PVI* is smaller than 10 points below the center. This variable is set to zero for other counties.	US Senate Lobbying data, LobbyView website, Cook Political Report, SoD
Bank-Level Variables		
BankPPPIntensity	Number of PPP loans a bank made in a quarter divided by the number of small businesses in that bank's counties, normalized to be in the [0,1] interval.	SBA, County Business Patterns, SoD
Capital Adequacy	Equity capital divided by *GTA*, normalized to be in the [0,1] interval.	Call Reports
Asset Quality	Loans and leases past due for at least ninety days or in nonaccrual status divided by *GTA*, normalized to be in the [0,1] interval.	Call Reports
Management Quality	Total interest and noninterest expense divided by *GTA*, normalized to be in the [0,1] interval.	Call Reports
Earnings	Net income divided by *GTA*, normalized to be in the [0,1] interval.	Call Reports
Liquidity	Cash divided by *GTA*, normalized to be in the [0,1] interval.	Call Reports
Sensitivity to Market Risk	Absolute difference between short-term assets and short-term liabilities divided by *GTA*, normalized to be in the [0,1] interval.	Call Reports
Bank Size	Natural logarithm of *GTA*. *GTA* equals total assets plus the allowance for loan and the lease losses and the allocated transfer risk reserve.	Call Reports
HHI	Herfindahl-Hirschman Index determined using the county bank deposits.	SoD
C&I Loans	Commercial and industrial loans (C&I) excluding PPP loans divided by *GTA*.	Call Reports
CRE Loans	Commercial real estate (CRE) loans divided by *GTA*.	Call Reports
Lerner Index	Price minus marginal cost of *GTA*, divided by price of *GTA*.	Call Reports
Market Share Assets	Market share of *GTA* in the bank's counties.	Call Reports, SoD
Market Share Loans	Market share of total loans in the bank's counties.	Call Reports, SoD
ROA	Net income divided by *GTA*, normalized to be in the [0,1] interval.	Call Reports
ROE	Net income divided by equity, normalized to be in the [0,1] interval.	Call Reports
BankCenter(bank)	Closeness of the banks' county's *PVI* to the center for values within the ±10 points around the center, normalized to be in the [0,1] interval.	Cook Political Report, SoD
BankRight(bank)	Closeness of the banks' county's *PVI* to the center for values greater than 10 points above the center, normalized to be in the [0,1] interval.	Cook Political Report, SoD
Variables for Bank Subsamples		
Smaller Banks	Banks with *GTA* less than or equal to $185 Million.	Call Reports
Larger Banks	Banks with *GTA* more than $185 Million.	Call Reports

Table 2: Role of Political Influences in PPP Bailouts – Main Evidence

This table presents main estimates from regressions analyzing the role of political influences in obtaining PPP funds. The dependent variable is the log odds variable, *ln(P/(1-P))*, where *P* is the number of PPP loans in a county divided by the number of small businesses in that county. The key independent variables are national and local political influences variables for the small businesses and banks in a county: *SmallBusCenter*: closeness of the small businesses' county's *PVI* to the center for values within ±10 points around the center, normalized to be in the [0,1] interval; *SmallBusRight*: closeness of the small businesses' county's *PVI* to the center for values greater than 10 points above the center, normalized to be in the [0,1] interval; *SmallBusLeft*: closeness of the small businesses' county's *PVI* to the center for values smaller than 10 points below the center, normalized to be in the [0,1] interval; *BankCenter*: closeness of the banks' county's *PVI* to the center for values within ±10 points around the center, normalized to be in the [0,1] interval; *BankRight*: closeness of the banks' county's *PVI* to the center for values greater than 10 points above the center, normalized to be in the [0,1] interval; *BankLeft*: closeness of the banks' county's *PVI* to the center for values smaller than 10 points below the center, normalized to be in the [0,1] interval; *SmallBusHSBComMem* and *BankHSBComMem*: take the value of *HSBComMem* if there is exactly one congressional district in the small businesses' or banks' county in 2019, respectively, and equals the average of *HSBComMem* in the county otherwise. The first six are proxies for national political influences while the last two are proxies for local political influences. All small business and bank political influences variables are measured prior to the PPP program start. We also include other county-level controls measured in 2019: *MSA, Unemployment Rate, % High Education, HPI House Index, % LMI*, and *% Minority*. All variables are defined in Table 1. Heteroskedasticity-robust *t*-statistics are reported in brackets unless noted otherwise in the specification. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Model	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	*ln(P/(1-P))*	*ln(P/(1-P))*	*ln(P/(1-P))*	*ln(P/(1-P))*	*ln(P/(1-P))*	*ln(P/(1-P))*
Independent Variables:						
SmallBusCenter	0.1441***	0.2124***			0.0580	0.0786
	[2.947]	[4.248]			[0.865]	[1.169]
SmallBusRight	0.1982***	0.2135***			-0.0369	-0.0140
	[3.655]	[3.940]			[-0.431]	[-0.163]
SmallBusLeft	-0.0307	-0.0948			-0.0803	-0.0246
	[-0.245]	[-0.744]			[-0.578]	[-0.176]
BankCenter			0.1980***	0.2659***	0.2297***	0.2363***
			[4.200]	[5.546]	[3.606]	[3.719]
BankRight			0.2513***	0.2467***	0.2813***	0.2630***
			[4.268]	[4.209]	[3.092]	[2.897]
BankLeft			0.0863	-0.0542	-0.0046	-0.0117
			[0.839]	[-0.509]	[-0.038]	[-0.097]
SmallBusHSBComMem						0.3072***
						[2.689]
BankHSBComMem						-0.1066
						[-0.781]
MSA		0.0045		0.0336	0.0350	0.0283
		[0.077]		[0.576]	[0.600]	[0.486]
Unemployment Rate		-7.4362***		-7.3961***	-7.3032***	-7.0621***
		[-5.554]		[-5.554]	[-5.459]	[-5.267]
% High Education		0.0136***		0.0142***	0.0144***	0.0147***
		[6.098]		[6.344]	[6.403]	[6.539]
HPI House Index		-0.0036		-0.0024	-0.0026	-0.0023
		[-0.882]		[-0.574]	[-0.625]	[-0.562]
% LMI		-0.2171**		-0.1997**	-0.1915*	-0.1875*
		[-2.141]		[-1.979]	[-1.891]	[-1.857]
% Minority		1.5280		1.5655	1.9830	3.1643
		[0.495]		[0.507]	[0.637]	[1.016]
Observations	3,138	3,138	3,138	3,138	3,138	3,138

Table 3: Role of Political influences in PPP Bailouts – The First Two PPP Waves

This table presents estimates from regressions analyzing the role of political influences in obtaining PPP funds looking separately at the initial and second waves of PPP. Specifically, Column (1) shows results for the initial wave, with the data before April 17, 2020; and Column (2) shows results for the second wave, with the data after April 26, 2020. In this table, the dependent variable is the log odds variable, *ln(P/(1-P))*, where *P* is the number of PPP loans in a county divided by the number of small businesses in that county. The key independent variables are national and local political influences variables for the small businesses and banks in a county: *SmallBusCenter*: closeness of the small businesses' county's *PVI* to the center for values within ±10 points around the center, normalized to be in the [0,1] interval; *SmallBusRight*: closeness of the small businesses' county's *PVI* to the center for values greater than 10 points above the center, normalized to be in the [0,1] interval; *SmallBusLeft*: closeness of the small businesses' county's *PVI* to the center for values smaller than 10 points below the center, normalized to be in the [0,1] interval; *BankCenter*: closeness of the banks' county's *PVI* to the center for values within ±10 points around the center, normalized to be in the [0,1] interval; *BankRight*: closeness of the banks' county's *PVI* to the center for values greater than 10 points above the center, normalized to be in the [0,1] interval; *BankLeft*: closeness of the banks' county's *PVI* to the center for values smaller than 10 points below the center, normalized to be in the [0,1] interval; *SmallBusHSBComMem* and *BankHSBComMem*: take the value of *HSBComMem* if there is exactly one congressional district in the small businesses' or banks' county in 2019, respectively, and equals the average of *HSBComMem* in the county otherwise. The first six are proxies for national political influences while the last two are proxies for local political influences All small business and bank political influences variables are measured prior to the PPP program start. We also include other county-level controls measured in 2019: *MSA, Unemployment Rate, % High Education, HPI House Index, % LMI*, and *% Minority*. All variables are defined in Table 1. Heteroskedasticity-robust *t*-statistics are reported in brackets unless noted otherwise in the specification. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Model	(1)	(2)
	Initial PPP Wave: Before April 17	Second PPP Wave: After April 26
Dependent Variable:	*ln(P/(1-P))*	*ln(P/(1-P))*
Independent Variables:		
SmallBusCenter	0.0342	0.0673
	[0.896]	[1.523]
SmallBusRight	-0.0183	-0.0548
	[-0.376]	[-0.972]
SmallBusLeft	0.1032	0.0937
	[1.304]	[1.023]
BankCenter	0.2249***	0.1355***
	[6.235]	[3.246]
BankRight	0.3441***	0.1847***
	[6.675]	[3.097]
BankLeft	-0.1041	0.1080
	[-1.531]	[1.373]
SmallBusHSBComMem	0.2187***	0.1150
	[3.371]	[1.532]
BankHSBComMem	-0.1196	-0.0685
	[-1.544]	[-0.765]
MSA	-0.0542	0.0916**
	[-1.638]	[2.391]
Unemployment Rate	-8.0880***	-6.2710***
	[-10.624]	[-7.120]
% High Education	0.0057***	0.0031**
	[4.457]	[2.114]
HPI House Index	-0.0032	-0.0039
	[-1.359]	[-1.456]
% LMI	-0.2015***	-0.3321***
	[-3.516]	[-5.008]
% Minority	-2.0804	2.8470
	[-1.176]	[1.392]
Observations	3,138	3,138

Table 4: Role of Political Influences in PPP Bailouts – Segmentation by Bank and Small Business Size

This table presents estimates from regressions analyzing the role of political influences in obtaining PPP funds for all counties in Column (1), for smaller and larger bank counties (below and above the median of smaller (< $100 Million GTA) bank share based on SoD) in Columns (2)-(3), and smaller and larger business counties (below and above the median of smaller (< 500 employees) small business share based on County Business Patterns) in Columns (4)-(5). The dependent variable is the log odds variable, *ln(P/(1-P))*, where *P* is the number of PPP loans in a county divided by the number of small businesses in that county. The key independent variables are national and local political influences variables for the small businesses and banks in a county: *SmallBusCenter*: closeness of the small businesses' county's *PVI* to the center for values within ±10 points around the center, normalized to be in the [0,1] interval; *SmallBusRight*: closeness of the small businesses' county's *PVI* to the center for values greater than 10 points above the center, normalized to be in the [0,1] interval; *SmallBusLeft*: closeness of the small businesses' county's *PVI* to the center for values smaller than 10 points below the center, normalized to be in the [0,1] interval; *BankCenter*: closeness of the banks' county's *PVI* to the center for values within ±10 points around the center, normalized to be in the [0,1] interval; *BankRight*: closeness of the banks' county's *PVI* to the center for values greater than 10 points above the center, normalized to be in the [0,1] interval; *BankLeft*: closeness of the banks' county's *PVI* to the center for values smaller than 10 points below the center, normalized to be in the [0,1] interval; *SmallBusHSBComMem* and *BankHSBComMem*: take the value of *HSBComMem* if there is exactly one congressional district in the small businesses' or banks' county in 2019, respectively, and equals the average of *HSBComMem* in the county otherwise. The first six are proxies for national political influences while the last two are proxies for local political influences All small business and bank political influences variables are measured prior to the PPP program start. We also include other county-level controls measured in 2019: *MSA, Unemployment Rate, % High Education, HPI House Index, % LMI*, and *% Minority*. All variables are defined in Table 1. Heteroskedasticity-robust *t*-statistics are reported in brackets unless noted otherwise in the specification. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Model	(1) All Counties	(2) Smaller Bank Counties	(3) Larger Bank Counties	(4) Smaller Business Counties	(5) Larger Business Counties
Dependent Variable:	*ln(P/(1-P))*	*ln(P/(1-P))*	*ln(P/(1-P))*	*ln(P/(1-P))*	*ln(P/(1-P))*
Independent Variables:					
SmallBusCenter	0.0786	0.0662	0.1329	0.0685	0.0619
	[1.169]	[0.749]	[1.306]	[0.789]	[0.694]
SmallBusRight	-0.0140	-0.0584	0.0623	-0.0435	0.1293
	[-0.163]	[-0.499]	[0.508]	[-0.435]	[0.813]
SmallBusLeft	-0.0246	-0.0481	-0.0233	-0.0367	-0.1242
	[-0.176]	[-0.252]	[-0.116]	[-0.183]	[-0.809]
BankCenter	0.2363***	0.2961***	0.0963	0.2630***	0.0792
	[3.719]	[3.564]	[0.990]	[3.212]	[0.879]
BankRight	0.2630***	0.2538**	0.2838**	0.2760***	0.0167
	[2.897]	[2.071]	[2.152]	[2.636]	[0.088]
BankLeft	-0.0117	-0.1463	0.2242	-0.0993	0.0176
	[-0.097]	[-0.942]	[1.199]	[-0.590]	[0.129]
SmallBusHSBComMem	0.3072***	0.4432***	0.0689	0.3791**	0.2297*
	[2.689]	[2.918]	[0.408]	[2.327]	[1.810]
BankHSBComMem	-0.1066	-0.2623	0.1487	-0.2223	0.0027
	[-0.781]	[-1.438]	[0.743]	[-1.180]	[0.016]
MSA	0.0283	0.0003	0.0757	-0.2119**	0.1809***
	[0.486]	[0.003]	[0.917]	[-2.435]	[2.789]
Unemployment Rate	-7.0621***	-8.7973***	-4.2461**	-8.5865***	-1.6218
	[-5.267]	[-5.113]	[-2.006]	[-5.566]	[-0.559]
% High Education	0.0147***	0.0152***	0.0128***	0.0095***	0.0172***
	[6.539]	[5.085]	[3.792]	[3.022]	[5.309]
HPI House Index	-0.0023	0.0026	-0.0127*	-0.0004	-0.0010
	[-0.562]	[0.506]	[-1.871]	[-0.090]	[-0.090]
% LMI	-0.1875*	-0.3181**	0.1388	-0.1671	0.3750
	[-1.857]	[-2.530]	[0.811]	[-1.442]	[1.627]
% Minority	3.1643	3.5107	1.7884	-11.2017*	2.5910
	[1.016]	[0.690]	[0.478]	[-1.880]	[0.876]
Observations	3,138	1,969	1,169	2,342	796

Table 5: Role of Political Influences in PPP Bailouts – Segmentation by Small Business Vulnerabilities

This table presents estimates from regressions analyzing the role of political influences in obtaining PPP funds when segmenting the data by small business vulnerabilities, below and above the median of *% LMI Counties* in Columns (1)-(2), *% COVID-19 Affected Industries* in the county in Columns (3)-(4), and *% COVID-19 Cases/100KPop* in Columns (5)-(6). The dependent variable is the log odds variable, *ln(P/(1-P))*, where *P* is the number of PPP loans in a county divided by the number of small businesses in that county. The key independent variables are national and local political influences variables for the small businesses and banks in a county: *SmallBusCenter*: closeness of the small businesses' county's *PVI* to the center for values within ±10 points around the center, normalized to be in the [0,1] interval; *SmallBusRight*: closeness of the small businesses' county's *PVI* to the center for values greater than 10 points above the center, normalized to be in the [0,1] interval; *SmallBusLeft*: closeness of the small businesses' county's *PVI* to the center for values smaller than 10 points below the center, normalized to be in the [0,1] interval; *BankCenter*: closeness of the banks' county's *PVI* to the center for values within ±10 points around the center, normalized to be in the [0,1] interval; *BankRight*: closeness of the banks' county's *PVI* to the center for values greater than 10 points above the center, normalized to be in the [0,1] interval; *BankLeft*: closeness of the banks' county's *PVI* to the center for values smaller than 10 points below the center, normalized to be in the [0,1] interval; *SmallBusHSBComMem* and *BankHSBComMem*: take the value of *HSBComMem* if there is exactly one congressional district in the small businesses' or banks' county in 2019, respectively, and equals the average of *HSBComMem* in the county otherwise. The first six are proxies for national political influences while the last two are proxies for local political influences All small business and bank political influences variables are measured prior to the PPP program start. We also include other county-level controls measured in 2019: *MSA, Unemployment Rate, % High Education, HPI House Index, % LMI*, and *% Minority*. All variables are defined in Table 1. Heteroskedasticity-robust *t*-statistics are reported in brackets unless noted otherwise in the specification. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Model	(1) Low % LMI Counties	(2) High % LMI Counties	(3) Low % COVID-19 Affected Industries	(4) High % COVID-19 Affected Industries	(5) Low % COVID-19 Cases/100KPop	(6) High % COVID-19 Cases/100KPop
Dependent Variable:	*ln(P/(1-P))*	*ln(P/(1-P))*	*ln(P/(1-P))*	*ln(P/(1-P))*	*ln(P/(1-P))*	*ln(P/(1-P))*
Independent Variables:						
SmallBusCenter	0.1848	-0.0007	0.1372	0.0757	0.0382	0.1180
	[1.552]	[-0.009]	[1.330]	[0.885]	[0.316]	[1.522]
SmallBusRight	-0.0099	-0.0283	-0.0056	0.0250	0.0762	-0.1381
	[-0.076]	[-0.250]	[-0.046]	[0.213]	[0.573]	[-1.130]
SmallBusLeft	-0.5028	0.0635	-0.1055	-0.0459	-0.3912	-0.0084
	[-1.622]	[0.415]	[-0.492]	[-0.258]	[-1.172]	[-0.061]
BankCenter	0.1899*	0.2918***	0.2239**	0.1753**	0.2924**	0.1447*
	[1.718]	[3.778]	[2.294]	[2.170]	[2.527]	[1.923]
BankRight	0.3157**	0.2561**	0.2415*	0.1686	0.1726	0.2732*
	[2.337]	[2.074]	[1.919]	[1.275]	[1.276]	[1.861]
BankLeft	0.1667	-0.1122	-0.1273	0.0486	-0.3526	0.0640
	[0.654]	[-0.846]	[-0.670]	[0.328]	[-1.299]	[0.525]
SmallBusHSBComMem	0.5843***	0.1947	0.1708	0.4382***	0.4546*	0.2361**
	[2.781]	[1.454]	[0.976]	[3.008]	[1.822]	[2.005]
BankHSBComMem	-0.3938	-0.0521	-0.0519	-0.0734	-0.3831	0.0678
	[-1.640]	[-0.312]	[-0.260]	[-0.401]	[-1.320]	[0.467]
MSA	-0.2285*	0.1300**	-0.1124	0.1083	-0.3760**	0.0903
	[-1.845]	[1.998]	[-1.074]	[1.614]	[-2.237]	[1.616]
Unemployment Rate	-13.4696***	-2.7014	-7.0752***	-5.6431**	-9.0572***	-3.9352**
	[-6.045]	[-1.620]	[-4.277]	[-2.311]	[-4.699]	[-1.965]
% High Education	0.0161***	0.0148***	0.0196***	0.0165***	0.0121**	0.0153***
	[4.187]	[5.258]	[5.331]	[5.506]	[2.476]	[6.009]
HPI House Index	0.0013	-0.0058	-0.0023	-0.0008	0.0025	-0.0119*
	[0.208]	[-1.099]	[-0.453]	[-0.111]	[0.427]	[-1.886]
% LMI	1.3986*	-0.7748***	-0.0035	-0.3138**	-0.2997**	0.3319**
	[1.655]	[-5.581]	[-0.025]	[-2.107]	[-2.010]	[2.185]
% Minority	-13.4785	3.8564	-2.7547	9.8751**	0.0515	5.0773
	[-1.483]	[1.190]	[-0.613]	[2.355]	[0.010]	[1.353]
Observations	1,207	1,931	1,727	1,411	1,451	1,432

Table 6: Role of Political Influences in PPP Bailouts – Lobbying as a Direct Mechanism

This table presents regressions analyzing lobbying as a direct mechanism for the national political influences of nonbank businesses and banks in influencing the distribution of PPP funds. The dependent variable is the log odds variable, *ln(P/(1-P))*, where *P* is the number of PPP loans in a county divided by the number of small businesses in that county. The key independent variables are lobbying intensity variables for the small businesses and banks in a county: *LobbyBusCenter* is the number of businesses that lobbied the federal government between 2016 and 2019 divided by the total number of businesses in center-leaning counties of the businesses that received PPP loans with PVI values within 10 points of the center. It is set to zero for right- and left-leaning counties further away from the center on the right and left. *LobbyBusRight,* and *LobbyBusLeft* are defined similarly for the other two sets of counties of these businesses. *LobbyBankCenter, LobbyBankRight,* and *LobbyBankLeft* are constructed analogously, but for the counties of the banks that distributed the PPP loans; *SmallBusHSBComMem* and *BankHSBComMem*: take the value of *HSBComMem* if there is exactly one congressional district in the small businesses' or banks' county in 2019, respectively, and equals the average of *HSBComMem* in the county otherwise. All small business and bank political influences variables are measured prior to the PPP program start. We also include other county-level controls measured in 2019: *MSA, Unemployment Rate, % High Education, HPI House Index, % LMI*, and *% Minority*. All variables are defined in Table 1. Heteroskedasticity-robust *t*-statistics are reported in brackets unless noted otherwise in the specification. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Model	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	*ln(P/(1-P))*	*ln(P/(1-P))*	*ln(P/(1-P))*	*ln(P/(1-P))*	*ln(P/(1-P))*	*ln(P/(1-P))*
Independent Variables:						
LobbyBusCenter	0.1106*	0.1734***			0.0524	0.0781
	[1.824]	[2.831]			[0.604]	[0.898]
LobbyBusRight	0.2202***	0.2269***			-0.0268	0.0016
	[3.028]	[3.128]			[-0.219]	[0.013]
LobbyBusLeft	-0.1303	-0.2252			-0.1733	-0.1144
	[-0.979]	[-1.625]			[-1.080]	[-0.710]
LobbyBankCenter			0.1385**	0.2009***	0.1610*	0.1547*
			[2.293]	[3.300]	[1.858]	[1.790]
LobbyBankRight			0.3021***	0.2845***	0.3115**	0.2851**
			[3.562]	[3.377]	[2.249]	[2.060]
LobbyBankLeft			-0.0296	-0.1536	-0.0827	-0.0997
			[-0.331]	[-1.623]	[-0.746]	[-0.895]
SmallBusHSBComMem						0.3205***
						[2.792]
BankHSBComMem						-0.1551
						[-1.135]
MSA		-0.0144		-0.0009	0.0010	-0.0047
		[-0.248]		[-0.015]	[0.018]	[-0.080]
Unemployment Rate		-7.8249***		-7.8694***	-7.7458***	-7.4869***
		[-5.844]		[-5.899]	[-5.782]	[-5.572]
% High Education		0.0127***		0.0128***	0.0131***	0.0133***
		[5.669]		[5.724]	[5.818]	[5.929]
HPI House Index		-0.0035		-0.0026	-0.0029	-0.0026
		[-0.849]		[-0.639]	[-0.701]	[-0.633]
% LMI		-0.2282**		-0.2291**	-0.2200**	-0.2169**
		[-2.248]		[-2.263]	[-2.167]	[-2.142]
% Minority		0.8564		0.6919	1.2811	2.2530
		[0.276]		[0.223]	[0.408]	[0.718]
Observations	3,138	3,138	3,138	3,138	3,138	3,138

Table 7: Banks' PPP Participation and Profitability (OLS and IV)

This table presents estimates from regressions analyzing the effects of PPP on bank profitability, using both an OLS approach in Panel A and an 2SLS IV approach in Panel B. Our sample spans 2019:Q1-2020:Q4. The dependent variable *ROA is* calculated as the net income divided by *GTA* and *ROE* is calculated as the net income to bank equity capital, both normalized to be in the [0,1] interval. The key independent variable is *BankPPPIntensity*, a bank's PPP lending intensity proxied by the number of PPP loans a bank made in a quarter divided by the number of small businesses in that bank's county. *BankPPPIntensity* is normalized to be within the range of [0, 1]. In Panel B, we report estimates from the second stage of an instrumental variable analysis, where we use as an instrument a bank political influences variable: *BankCenter(bank)*, the closeness of the banks' county's PVI to the center for values within the ±10 point around the center and normalized to be in the [0,1] interval. In all regressions, we also include other bank characteristics: proxies for CAMELS (*Capital Adequacy*, *Asset Quality*, *Management Quality*, *Earnings*, *Liquidity*, and *Sensitivity to Market Risk*), *Bank Size*, and *HHI*. All regressions include Bank and Year-Quarter FE unless noted otherwise. All variables are defined in Table 1. Heteroskedasticity-robust *t*-statistics are reported in brackets unless noted otherwise. The *tF*-statistics are reported in curly brackets. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: OLS Results

Model	(1) All Banks	(2) Smaller Banks	(3) Larger Banks	(1) All Banks	(2) Smaller Banks	(3) Larger Banks
Dependent Variable:	*ROA*	*ROA*	*ROA*	*ROE*	*ROE*	*ROE*
Independent Variables:						
BankPPPIntensity	0.0222***	0.0401***	0.0145***	0.0430***	0.0849***	0.0272***
	[6.305]	[5.689]	[3.695]	[8.156]	[8.297]	[4.530]
Capital Adequacy	0.0329***	0.0435***	0.0382***	-0.4068***	-0.3007***	-0.5873***
	[7.049]	[7.084]	[4.759]	[-58.149]	[-33.760]	[-47.726]
Asset Quality	-0.0184***	-0.0214***	-0.0099***	-0.0624***	-0.0646***	-0.0459***
	[-8.974]	[-7.775]	[-3.107]	[-20.318]	[-16.201]	[-9.423]
Management Quality	0.1596***	0.1604***	0.1593***	0.1125***	0.0957***	0.1250***
	[32.015]	[23.139]	[21.870]	[15.063]	[9.521]	[11.210]
Earnings	0.5934***	0.5802***	0.5996***	0.7733***	0.7073***	0.8343***
	[148.542]	[101.553]	[106.715]	[129.214]	[85.355]	[96.941]
Liquidity	0.0020	0.0020	0.0019	-0.0064**	-0.0197***	0.0108***
	[1.094]	[0.746]	[0.803]	[-2.367]	[-4.991]	[2.939]
Sensitivity to Market Risk	-0.0034*	-0.0046	0.0070***	0.0066**	0.0056	0.0245***
	[-1.749]	[-1.622]	[2.617]	[2.294]	[1.366]	[5.998]
Bank Size	0.0035***	0.0116***	0.0004	0.0073***	0.0256***	0.0000
	[14.291]	[12.885]	[1.192]	[19.580]	[19.622]	[0.056]
HHI	0.0027**	0.0025	0.0039**	0.0068***	0.0052*	0.0097***
	[2.163]	[1.253]	[2.539]	[3.631]	[1.794]	[4.091]
Bank, Year-Quarter FE	YES	YES	YES	YES	YES	YES
Observations	41,202	19,709	21,767	41,202	19,709	21,767

Panel B: IV (2nd stage) Results

Model	(1) All Banks	(2) Smaller Banks	(3) Larger Banks	(1) All Banks	(2) Smaller Banks	(3) Larger Banks
Dependent Variable:	*ROA*	*ROA*	*ROA*	*ROE*	*ROE*	*ROE*
Independent Variables:						
BankPPPIntensity	0.6525***	1.1783***	0.5302***	1.3108***	2.1293***	1.0759***
	[10.875]	[5.269]	[8.871]	[12.558]	[5.745]	[10.062]
tF-statistics	{10.875}	{3.824}	{8.079}	{12.558}	{4.170}	{9.273}
Capital Adequacy	0.0534***	0.0753***	0.0575***	-0.3703***	-0.2505***	-0.5456***
	[8.194]	[6.832]	[5.186]	[-32.644]	[-13.708]	[-27.932]
Asset Quality	-0.0223***	-0.0253***	-0.0182***	-0.0705***	-0.0715***	-0.0638***
	[-7.970]	[-5.866]	[-4.046]	[-14.488]	[-10.007]	[-8.075]
Management Quality	0.1678***	0.1830***	0.1591***	0.1295***	0.1388***	0.1239***
	[24.901]	[15.833]	[16.181]	[11.044]	[7.247]	[7.154]
Earnings	0.5681***	0.5347***	0.5724***	0.7238***	0.6271***	0.7792***
	[96.054]	[42.406]	[69.311]	[70.331]	[30.009]	[53.545]
Liquidity	0.0033	0.0006	0.0026	-0.0038	-0.0220***	0.0119**
	[1.343]	[0.135]	[0.811]	[-0.889]	[-3.172]	[2.087]
Sensitivity to Market Risk	0.0082***	-0.0020	0.0236***	0.0301***	0.0110	0.0591***
	[2.881]	[-0.448]	[5.695]	[6.118]	[1.505]	[8.051]
Bank Size	-0.0008	0.0009	-0.0024***	-0.0014	0.0064	-0.0057***
	[-1.489]	[0.356]	[-4.159]	[-1.508]	[1.535]	[-5.464]
HHI	-0.0263***	-0.0252***	-0.0289***	-0.0516***	-0.0448***	-0.0571***
	[-8.092]	[-3.980]	[-6.672]	[-9.121]	[-4.267]	[-7.391]

Bank, Year-Quarter FE	YES	YES	YES	YES	YES	YES
Observations	40,122	19,269	21,127	40,122	19,269	21,539

Table 8: Banks' PPP Participation and Profitability Drivers (OLS and IV)

This table presents estimates from regressions analyzing the effects of PPP on drivers of bank profitability for all banks, using both an OLS approach in Panel A and an 2SLS IV approach in Panel B. Our sample spans 2019:Q1-2020:Q4. The dependent variables are one of the following components of bank *ROA:* net interest income, net non-interest income, gains and losses from trading securities, loan loss provisions, and taxes, all divided by GTA; all components are normalized to be in the [0,1] interval. The key independent variable is *BankPPPIntensity*, a bank's PPP lending intensity proxied by the number of PPP loans a bank made in a quarter divided by the number of small businesses in that bank's county. *BankPPPIntensity* is normalized to be within the range of [0, 1]. In Panel B, we report estimates from the second stage of an instrumental variable analysis, where we use as an instrument a bank political influences variable: *BankCenter(bank)*, the closeness of the banks' county's PVI to the center for values within the ±10 point around the center and normalized to be in the [0,1] interval. In all regressions, we also include other bank characteristics: proxies for CAMELS (*Capital Adequacy*, *Asset Quality*, *Management Quality*, *Earnings*, *Liquidity*, and *Sensitivity to Market Risk*), *Bank Size*, and *HHI*. All regressions include Bank and Year-Quarter FE unless noted otherwise. All variables are defined in Table 1. Heteroskedasticity-robust *t*-statistics are reported in brackets unless noted otherwise. The *tF*-statistics are reported in curly brackets. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: OLS Results

Model	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	*Net Interest Income*	*Net Non-Interest Income*	*Trading Securities G&L*	*Loan Loss Provisions*	*Taxes*
Independent Variables:					
BankPPPIntensity	0.0011***	-0.0011	0.009	0.0606***	-0.0165***
	[9.202]	[-1.095]	[1.424]	[9.320]	[-3.684]
Capital Adequacy	-0.0032***	0.0043***	-0.0553***	0.0643***	0.2529***
	[-19.758]	[3.245]	[-6.604]	[7.456]	[42.723]
Asset Quality	0.0010***	-0.0003	0.0127***	0.1219***	-0.0179***
	[13.621]	[-0.454]	[3.456]	[32.225]	[-6.901]
Management Quality	-0.0005***	0.0606***	0.0183**	0.0272***	0.2296***
	[-3.137]	[42.601]	[2.049]	[2.954]	[36.324]
Earnings	0.0061***	0.0314***	-0.0285***	-0.0175**	0.2698***
	[43.231]	[27.509]	[-3.974]	[-2.375]	[53.284]
Liquidity	-0.0038***	0.0071***	0.1148***	-0.0930***	-0.0408***
	[-59.197]	[13.818]	[35.387]	[-27.869]	[-17.812]
Sensitivity to Market Risk	-0.0006***	0	-0.0220***	-0.0022	0.0066***
	[-8.331]	[-0.071]	[-6.400]	[-0.625]	[2.703]
Bank Size	-0.0001***	0.0004***	0.0005	0.0194***	0.0175***
	[-7.575]	[5.187]	[1.137]	[42.449]	[55.820]
HHI	0.0003***	0	0.0029	-0.0031	-0.0031*
	[7.206]	[0.009]	[1.279]	[-1.331]	[-1.942]
Bank, Year-Quarter FE	YES	YES	YES	YES	YES
Observations	41,202	41,202	41,202	41,202	41,202

Panel B: IV (2nd stage) Results

Model	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	*Net Interest Income*	*Net Non-Interest Income*	*Trading Securities G&L*	*Loan Loss Provisions*	*Taxes*
Independent Variables:					
BankPPPIntensity	0.0319***	-0.0254*	-0.1778**	0.9074***	-0.3225***
	[12.742]	[-1.939]	[-2.173]	[9.172]	[-5.345]
tF-statistics	{12.742}	{-1.939}	{-2.173}	{9.172}	{-5.345}
Capital Adequacy	-0.0024***	0.0035**	-0.0625***	0.0855***	0.2473***
	[-8.819]	[2.453]	[-7.033]	[7.952]	[37.729]
Asset Quality	0.0008***	-0.0001	0.0139***	0.1194***	-0.0155***
	[7.015]	[-0.134]	[3.652]	[25.871]	[-5.525]
Management Quality	-0.0001	0.0605***	0.0151	0.0393***	0.2240***
	[-0.240]	[41.109]	[1.642]	[3.538]	[33.064]
Earnings	0.0048***	0.0326***	-0.0190**	-0.0501***	0.2827***
	[19.643]	[25.265]	[-2.360]	[-5.140]	[47.536]
Liquidity	-0.0037***	0.0071***	0.1169***	-0.0901***	-0.0409***
	[-36.102]	[13.355]	[35.057]	[-22.343]	[-16.625]
Sensitivity to Market Risk	0.0001	-0.0005	-0.0242***	0.0155***	0.0018
	[0.585]	[-0.773]	[-6.267]	[3.324]	[0.644]
Bank Size	-0.0003***	0.0005***	0.0018**	0.0139***	0.0197***
	[-12.164]	[4.558]	[2.541]	[15.819]	[36.868]
HHI	-0.0011***	0.0011	0.0114**	-0.0420***	0.0101***

	[-8.262]	[1.616]	[2.561]	[-7.844]	[3.094]
Bank, Year-Quarter FE	YES	YES	YES	YES	YES
Observations	40,122	40,122	40,122	40,122	40,122

Table 9: Banks' PPP Participation and C&I and CRE Lending (OLS and IV)

This table presents estimates from regressions analyzing the effects of PPP on bank C&I and CRE lending using both an OLS approach in Panel A and an 2SLS IV approach in Panel B. Our sample spans 2019:Q1-2020:Q4. The dependent variables are *C&I Loans*, commercial and industrial loans excluding PPP loans divided by *GTA,* and *CRE Loans*, commercial real estate loans divided by *GTA*. The key independent variable is *BankPPPIntensity*, a bank's PPP lending intensity proxied by the number of PPP loans a bank made in a quarter divided by the number of small businesses in that bank's county. *BankPPPIntensity* is normalized to be within the range of [0, 1]. In Panel B, we report estimates from the second stage of an instrumental variable analysis, where we use as an instrument a bank political influences variable: *BankCenter(bank)*, the closeness of the banks' county's PVI to the center for values within the ±10 point around the center and normalized to be in the [0,1] interval. In all regressions, we also include other bank characteristics: proxies for CAMELS (*Capital Adequacy*, *Asset Quality*, *Management Quality*, *Earnings*, *Liquidity*, and *Sensitivity to Market Risk*), *Bank Size*, and *HHI*. All regressions include Bank and Year-Quarter FE unless noted otherwise. All variables are defined in Table 1. Heteroskedasticity-robust *t*-statistics are reported in brackets unless noted otherwise. The tF-statistics are reported in curly brackets. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: OLS Results

Model	(1) All Banks	(2) Smaller Banks	(3) Larger Banks	(1) All Banks	(2) Smaller Banks	(3) Larger Banks
Dependent Variable:	*C&I Loans*	*C&I Loans*	*C&I Loans*	*CRE Loans*	*CRE Loans*	*CRE Loans*
Independent Variables:						
BankPPPIntensity	0.0585***	0.0877***	0.0405***	0.0082***	0.0130***	0.0055***
	[13.677]	[11.182]	[7.619]	[13.695]	[11.940]	[7.362]
Capital Adequacy	-0.0528***	-0.0156**	-0.0957***	-0.0046***	-0.0005	-0.0109***
	[-9.311]	[-2.288]	[-8.808]	[-5.881]	[-0.489]	[-7.157]
Asset Quality	-0.0048*	-0.0030	-0.0053	0.0001	0.0003	-0.0001
	[-1.948]	[-0.977]	[-1.243]	[0.253]	[0.647]	[-0.237]
Management Quality	-0.0194***	-0.0017	-0.0504***	-0.0030***	-0.0014	-0.0062***
	[-3.201]	[-0.225]	[-5.119]	[-3.598]	[-1.335]	[-4.544]
Earnings	0.0153***	-0.0221***	0.0388***	0.0019***	-0.0020**	0.0048***
	[3.155]	[-3.483]	[5.098]	[2.795]	[-2.274]	[4.547]
Liquidity	-0.0966***	-0.0830***	-0.1128***	-0.0108***	-0.0085***	-0.0137***
	[-44.056]	[-27.435]	[-34.903]	[-35.305]	[-20.276]	[-30.330]
Sensitivity to Market Risk	0.0059**	-0.0019	0.0307***	0.0024***	0.0010**	0.0056***
	[2.521]	[-0.605]	[8.512]	[7.530]	[2.302]	[11.206]
Bank Size	0.0067***	0.0140***	0.0029***	0.0011***	0.0013***	0.0008***
	[22.319]	[13.963]	[6.044]	[25.820]	[9.565]	[12.361]
HHI	-0.0134***	-0.0110***	-0.0137***	-0.0020***	-0.0014***	-0.0023***
	[-8.867]	[-4.959]	[-6.541]	[-9.380]	[-4.561]	[-7.741]
Bank, Year-Quarter FE	YES	YES	YES	YES	YES	YES
Observations	41,202	19,709	21,767	41,202	19,709	21,767

Panel B: IV (2nd stage) Results

Model	(1) All Banks	(2) Smaller Banks	(3) Larger Banks	(1) All Banks	(2) Smaller Banks	(3) Larger Banks
Dependent Variable:	*C&I Loans*	*C&I Loans*	*C&I Loans*	*CRE Loans*	*CRE Loans*	*CRE Loans*
Independent Variables:						
BankPPPIntensity	0.3700***	0.5012**	0.3484***	0.0560***	0.1117***	0.0465***
	[6.343]	[2.864]	[5.343]	[6.813]	[4.123]	[5.138]
tF-statistics	{6.343}	{2.079}	{4.866}	{6.813}	{2.992}	{4.679}
Capital Adequacy	-0.0415***	-0.0030	-0.0817***	-0.0030***	0.0023*	-0.0090***
	[-6.550]	[-0.344]	[-6.750]	[-3.353]	[1.719]	[-5.381]
Asset Quality	-0.0070***	-0.0052	-0.0101**	-0.0002	-0.0002	-0.0008
	[-2.584]	[-1.547]	[-2.048]	[-0.643]	[-0.366]	[-1.125]
Management Quality	-0.0151**	0.0072	-0.0513***	-0.0023**	0.0007	-0.0064***
	[-2.312]	[0.801]	[-4.784]	[-2.535]	[0.494]	[-4.275]
Earnings	-0.0004	-0.0434***	0.0213**	-0.0005	-0.0066***	0.0025**
	[-0.078]	[-4.398]	[2.364]	[-0.623]	[-4.330]	[1.978]
Liquidity	-0.0964***	-0.0844***	-0.1130***	-0.0107***	-0.0087***	-0.0137***
	[-40.577]	[-25.705]	[-31.818]	[-32.021]	[-17.192]	[-27.781]
Sensitivity to Market Risk	0.0126***	-0.0008	0.0424***	0.0034***	0.0013**	0.0072***
	[4.569]	[-0.218]	[9.389]	[8.860]	[2.350]	[11.482]

Bank Size	0.0050***	0.0103***	0.0016**	0.0008***	0.0004	0.0007***
	[9.601]	[5.173]	[2.563]	[11.078]	[1.379]	[7.533]
HHI	-0.0271***	-0.0202***	-0.0328***	-0.0041***	-0.0037***	-0.0048***
	[-8.579]	[-4.069]	[-6.936]	[-9.174]	[-4.836]	[-7.299]
Bank, Year-Quarter FE	YES	YES	YES	YES	YES	YES
Observations	40,122	19,269	21,127	40,122	19,269	21,127

Author Credit Statement

Allen N. Berger
All aspects of the paper

Mustafa U. Karakaplan
All aspects of the paper

Raluca A. Roman
All aspects of the paper