Ashoka University
Economics Discussion Paper 134

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November 2024

Deniz Igan, International Monetary Fund and CEPR
Thomas Lambert, Erasmus University
Prachi Mishra, Department of Economics and the Isaac Center for Public Policy, Ashoka University
Eden Zhang, Monash University

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The Politics of the Paycheck Protection Program

Deniz Igan, Thomas Lambert, Prachi Mishra, and Eden Zhang*

November 14, 2024

Abstract

Does partisanship influence loan allocation through the Paycheck Protection Program (PPP)? We examine the 2020 Presidential campaign contributions by lenders' employees as a measure of partisanship and leverage the staggered rollout of the PPP under both Trump and Biden administrations to address this question. We find that partisan misalignment increases bank lending, particularly to small and first-time PPP borrowers, and those in Republican areas. This is consistent with Republican-leaning banks viewing the PPP's 2021 phase as a legacy policy of the prior administration. Using county-level weekly unemployment insurance data, we also show that partisan misalignment is associated with higher PPP payroll coverage for small businesses. Our findings shed new light on the partisan-alignment phenomenon in finance.

JEL classification codes: D72, G21, G28, G32, G38, H12, H81

Keywords: COVID-19, government aid program, lending, partisanship, Paycheck Protection Program, political polarization

* Igan is with the International Monetary Fund and CEPR, 700 19th Street NW, Washington, DC, 20431, United States, email: digan@imf.org. Lambert is with Rotterdam School of Management, Erasmus University, Burgemeester Oudlaan 50, 3062 PA Rotterdam, Netherlands, email: t.lambert@rsm.nl. Mishra is with Isaac Center for Public Policy, Ashoka University, Plot No. 2, Rajiv Gandhi Education City, National Capital Region P.O. Rai, Sonepat Haryana-131029, India, email: prachi.mishra@ashoka.edu.in. Zhang is with Monash Business School, Monash University, 900 Dandenong Road, Caulfield East VIC 3145, Australia, email: eden.zhang@monash.edu. We are extremely grateful to Sergey Chernenko (our discussant and referee), Stijn Claessens, Andrew Ellul and Isil Erel (the editors), Nandini Gupta, and participants at the 2022 AEA Meeting and the 2024 RCFS Winter Conference for their comments and suggestions. Lambert received the support of the Dutch Research Council (NWO) for this project (grant VI.Veni.191E.055). The views expressed here are those of the authors and do not necessarily reflect those of the International Monetary Fund.

1. Introduction

The COVID-19 outbreak triggered an unprecedented economic freeze that left millions of businesses in dire need of liquidity (Bartik et al., 2020a). The government aid response around the world was immediate and unprecedented. In the United States, as a centerpiece of the Coronavirus Aid, Relief, and Economic Security (CARES) Act of 2020, the Paycheck Protection Program (PPP) aimed to provide financial assistance to businesses that were hit hardest by the freeze. The PPP provided a temporary source of liquidity for small businesses, initially authorizing $659 billion in forgivable loans and guarantees. This first phase of PPP ran between April and August 2020. As a follow-on response to the outbreak, in January 2021, the Consolidated Appropriations Act (CAA) of 2021 included $284 billion in additional forgivable loans for a second phase of PPP.

In this paper, we examine whether lenders' partisanship plays a role in shaping lending within the PPP, which was carried out during a period of intense political polarization in the United States.[1] Although the Small Business Administration (SBA) issued loan guarantees and ultimately determined loan forgiveness, PPP loans were processed and delivered through the nation's financial system. Without the deployment of private lenders, it would have been impossible to distribute billions of dollars in loans to millions of borrowers within a few months. While lenders were bound by the borrower eligibility rules outlined in the PPP, they retained discretion in processing and approving applications.[2] Both their capacity—such as the ability to meet capital and liquidity requirements set by federal regulators—and their willingness to engage in PPP lending were critical factors. This willingness may have stemmed from a desire to maintain existing client relationships or, potentially, from partisan motivations. For instance, lenders may derive utility from supporting policies of an administration aligned with their political leanings, or they may share beliefs or preferences with the administration regarding the PPP's objectives. Whether, and to what extent, partisan alignment influenced PPP implementation is the focus of this paper.

Isolating the effect of partisanship on PPP fund allocation decisions is empirically challenging for two main reasons. First, partisan alignment between a lender and the ruling administration could correlate

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[1] In 2019, 82 percentage points separated Republicans' (89%) and Democrats' (7%) average job approval ratings of President Trump, which is the largest degree of political polarization in any presidential year measured by Gallup until then (see https://news.gallup.com/poll/283910/trump-third-year-sets-new-standard-party-polarization.aspx; last accessed: December 1, 2023). By 2021, a new record of 84 percentage points separated Republicans' (8%) and Democrats' (92%) average job approval ratings of President Biden. Coibion et al. (2020) report large-scale survey evidence of the effects of political polarization on economic expectations: both Republicans and Democrats expect their preferred candidate to win with a very high probability, and they expect the economy to perform poorly when the candidate of the opposing party wins.

[2] Guidance by the SBA allowed all loans to be processed by all lenders under delegated authority and relying on certifications of the borrower in order to determine eligibility of the borrower and the use of loan proceeds.

with other (omitted) factors of proximity between lenders and the administration. Second, the need for PPP funds or the severity of the pandemic may be directly affected by changes in government policies or political uncertainty surrounding the presidential election. We address these challenges by leveraging the staggered rollout of PPP around the 2020 presidential election. While both economic relief packages under the PPP were enacted during the Trump administration, the disbursement of loans in the program's second phase occurred under the Biden administration. This shift in partisan alignment between PPP lenders and the administration in charge began in early 2021, following the close 2020 presidential election. Therefore, the transition between administrations during the PPP's rollout provides a unique opportunity to identify whether partisan (mis)alignment between lenders and the governing administration affected lending decisions.

The question we raise in this context is whether and how Republican-leaning lenders behaved differently than their Democrat-leaning counterparts, controlling for other observable differences between the two groups. Did Republican-leaning lenders perceive the second phase under the Biden administration, with whom they were not aligned, as a less appealing part of their portfolio, leading to reduced enthusiasm in PPP lending compared to Democrat-leaning lenders? This "contemporaneous-alignment" view suggests a *negative* association between partisan misalignment and PPP lending. Such an association may exist because lenders derive disutility from engaging with an administration from the opposing camp or they disagree with the administration in control about the objectives and risks of the program or the broader economic outlook.[3] Conversely, did Republican-leaning lenders view the second phase of the PPP still as a policy of the Trump administration, with which they were more aligned, and extend more loans than their Democrat-leaning counterparts? This "legacy-policy" view suggests a *positive* association between partisan misalignment and PPP lending.

To establish our results, we construct a balanced panel data set by aggregating partisan PPP lenders' lending activities to calendar weeks spanning both phases of PPP. We obtain PPP data from the SBA. Our sample consists of 2,551 lenders over 38 weeks (18 weeks in 2020 and 20 weeks in 2021), who extend an average (median) of 42.9 (6) loans per week amounting to $3.6 million ($141 thousand). To measure lender partisanship, we adopt a "bottom-up" (employee-level) approach using campaign contributions made by a lender's employees. Specifically, we use lender employees' individual contributions to political action committees (PACs) and candidates in the 2020 election cycle.[4] This

[3] See Kempf and Tsoutsoura (2024) for more on the "partisan utility" and "partisan belief" mechanisms through which partisan alignment may influence agents' decisions.
[4] Measuring partisanship using data from the 2020 cycle is ideal for this study for three reasons. First, our identification strategy exploits the outcome of the 2020 election cycle as an exogenous shock; hence, it would be plausible use contributions made during this cycle

approach has the advantage of reflecting the underlying political views of people that constitute the organization. For the election cycle we study, we can also include small individual contributions (below $200) since ActBlue and WinRed (crowdfunding platforms for political donations) required identity disclosure. This allows us to address potential concerns about data scarcity on campaign contributions made by individual employees. Most lenders lean as Republicans, with 67% of their employees supporting the Republican party and candidates. For robustness purposes, we also measure lender partisanship using a "top-down" approach using campaign contributions made by lenders as legal entities. About 70% of lenders contribute to the campaigns of Republicans.

In a difference-in-differences research design, we find that Republican-leaning lenders engaged in greater PPP lending during the program's second phase—that is, under the Biden administration. The effect is economically meaningful: a Republican-leaning lender in the 75th percentile of the partisanship distribution increases its weekly lending volume by 24.3% more in the PPP's second phase compared to a neutral lender in the 25th percentile and its number of new loans by 9.8% more.[5]

This positive relationship between partisan misalignment and PPP lending is consistent with the "legacy-policy" view. Several explanations may be driving this finding, although we cannot fully disentangle them. One possible explanation is that Republican-leaning lenders viewed the PPP as a legacy of the Trump administration and, motivated by a desire to preserve political capital and maintain connections with their Republican co-partisans, increased their lending even under a politically misaligned administration. Another, non-mutually exclusive explanation is that the effect of partisan alignment on lending may depend on who ultimately bears the credit risk. In contrast to previous study settings where lenders assume this risk, PPP loans are forgivable, thus placing the cost of defaults on the administration in charge. This distinction suggests that partisan alignment's effect on lending may hinge on whether the lender or the government assumes the credit risk. When it is the lenders, partisanship may offer them benefits that offset costs or shape their risk perceptions, thereby creating a divide between the behaviors of politically aligned and misaligned lenders. When it is the government, the cost-benefit calculation changes. Consequently, misaligned lenders may adopt more

itself, rather than say during previous cycles. Second, campaign contributions may not be persistent (see, for example, Rueda and Ruiz, 2021), and therefore, employing contributions from previous cycles may not accurately reflect partisanship during the 2020 elections. Third, the individual contribution records from the 2020 cycle have the advantage of including a vast number of small donor contributions by employees, which allows to go into the detailed record of individual contribution data to identify lender employee ideology.

[5] Our specifications control for various bank characteristics, political and institutional factors, and lender and week fixed effects. Our results also remain robust in a matched sample based on propensity scores.

aggressive lending strategies, potentially draining the resources of an ideologically distant administration.

We conduct additional tests to ensure our results genuinely reflect partisanship rather than other potential mechanisms that could produce a positive correlation between partisan misalignment and PPP lending. We find that the partisanship of rank-and-file employees—those with direct discretion in granting loans—matters most, as opposed to executives who are less likely to be involved in individual lending decisions. The relationship is also primarily driven by loans granted to small and first-time borrowers under the program ("first-draw loans"). These are the cases where loan officers are more likely to have leeway in applying judgment due to limited standardized or recent information on the borrower's capacity to repay. Furthermore, our results indicate that partisan misalignment during the program's second phase is associated with relatively higher allocation of PPP funds in counties that are typically considered to be Republican strongholds. Republican-leaning lenders expanded their PPP lending more significantly in counties with a larger white population, lower personal income per capita, and a workforce less suited to teleworking. Republican-leaning lenders also mainly direct loans to borrowers in Republican-voting states. If anything, these further tests are in line with these lenders seeing the PPP as a legacy of the Trump administration and looking to maintain ties with their co-partisans.

Does partisan misalignment ultimately matter? To shed some light on this question, we investigate the real and aggregate effects. First, with county-level weekly unemployment insurance (UI) data, we present evidence that partisan misalignment is associated with higher PPP payroll coverage for small businesses. This underscores that partisan misalignment has real effects that goes beyond its direct effects on PPP loan origination. Second, by collapsing our data set at the county level, we document that the effect of partisan misalignment translates meaningfully at the county level: a county with Republican-leaning lenders (with average 78.4% Republican-leaning employees at the 75th percentile) experiences a weekly PPP lending growth rate that is 32.26% higher than a county with a "neutral" lender (defined as a lender with 50.5% Republican-leaning employees at the 25th percentile); and its number of new loans increases by 12% more county-wide.

Our findings hold significant implications for both research and policy. First, we contribute to the literature on political polarization and finance, providing evidence that partisan misalignment may actually incentivize lending activities within the PPP context rather than holding loans back. These findings complement prior work on political polarization in banking by suggesting a new dimension to consider: who ultimately bears the risk may matter for the partisan-alignment phenomenon. In the specific PPP context, it is the government that assumes the credit risk, while banks are making decisions to grant credit. Second, we show the importance of accounting for small donor contributions by employees in measuring lender partisanship, which may better capture the intensity of political engagement and influence within organizations. Last, we add to the growing body of literature on politics and banking by uncovering novel evidence of “more benign” effects of political-economy factors on small business lending in the context of one of the largest economic relief packages in recent history.

2. Literature Review

Our paper contributes to several strands of the economics and finance literature. First, it is related to work on the political economy of government aid programs. Several studies examine whether electoral politics affects the spatial allocation of government funds: Fishback et al. (2003) focus on funds under the New Deal in the 1930s, Boone et al. (2014) under the American Recovery and Reinvestment Act of 2009, Duchin and Hackney (2021) and Berger et al. (2023) under the first phase of PPP in 2020, and Ha (2024) under the second phase of PPP in 2021. Unlike these papers that examine the aggregate spatial allocation of funds across states or counties, our analysis operates at the lender level. We focus specifically on the political motivation behind lending decisions in a highly polarized political context, uncovering that partisan misalignment between lenders and the administration positively influences support for small businesses during both phases of PPP.

Second, our paper adds to the literature on the relation between partisanship and economic behaviors, including that of loan officers (Dagostino et al., 2023), credit analysts (Kempf and Tsoutsoura, 2021), entrepreneurs (Engelberg et al., 2023), professional money managers (Cassidy and Vorsatz, 2021), judges (Chen, 2020), and central bankers (Ioannidou et al., 2023).[6] One of the closest to our line of inquiry is Kempf et al. (2023), who find that ideological alignment between US banks and foreign governments is an important factor behind the allocation of cross-border syndicated loans to corporations. In a similar spirit, we infer partisan leaning of lenders using their political contributions to candidates running in the 2020 presidential election to identify whether partisan alignment shapes the allocation of PPP funds. We expand on this study by measuring partisanship through the individual contributions of lender employees to political candidates. This approach is crucial, as aggregated individual contributions contribute to the “bottom-up” partisanship of organizations. Additionally, our measures of partisanship consider small individual contributions (under $200) because both major

[6] See Kempf and Tsoutsoura (2024) for a survey of the literature on political polarization and finance.

platforms for individual contributions, ActBlue and WinRed, required identity disclosure during the election cycle we examine (Bouton et al., 2022; Cagé, 2024). This inclusion is an improvement over much of the existing literature on politics and finance, which often overlooks these smaller contributions. Including them allows us to capture a more comprehensive view of partisanship and further mitigate concerns about data scarcity. Interestingly, our results also contrast with prior studies that show partisan misalignment negatively impacts lending, which are supported by explanations centered on partisan utility or partisan beliefs (e.g., Dagostino et al., 2023; Kempf et al., 2023). Our results rather indicate that partisan misalignment between lenders and the administration increases PPP lending, consistent with the idea that Republican-leaning lenders may have still viewed the program's second phase as part of the Trump administration's agenda. As a result, they may have increased their PPP lending to preserve or even enhance their political capital under the new, misaligned administration. Our findings thus complement these prior studies on political polarization and banking.

Third, our paper belongs to the broader literature on politics and credit.[7] Within this literature, our paper is most closely related to studies documenting the influence of banks' political connections on loan renegotiations (Agarwal et al. 2018), mortgage lending (Chavaz and Rose 2019), consumer lending (Akey et al., 2021), and corporate lending (Lambert et al., 2023) in the United States. Our paper documents effects of politics on small business lending (PPP loans), while contributing to our understanding of the mechanisms behind the partisan-alignment phenomenon.

Last, our paper is connected to a rapidly growing literature on the determinants of PPP allocation (Bayluk et al., 2021; Cororaton and Rosen, 2021; Li and Strahan, 2021; Granja et al., 2022; Chernenko and Scharfstein, 2024) and its impacts on the US economy (Bartik et al., 2020a, 2020b; Chetty et al., 2020; Hanson et al., 2020; Humphries et al., 2020; Meier and Smith, 2020; Bartlett and Morse, 2021; Granja et al., 2021; Autor et al., 2022b; Chodorow-Reich et al., 2022; Elenev et al., 2022). We join this literature by presenting novel evidence on the extent to which lenders' partisan alignment with the administration influences the allocation of PPP funds and produces real effects.

3. Background and Data

3.1. Timeline of the PPP

Our empirical strategy leverages the staggered implementation of the PPP around the closely contested presidential election of 2020. Below, we outline the timeline of the PPP under both the Trump and

[7] See Lambert and Volpin (2018) for a survey of the literature on political economy and (bank) finance.

Biden administrations. For a detailed description of the PPP rounds and their targeting, we refer to prior work on the PPP (e.g., Autor et al., 2022a).

- **Phase 1 ("Trump").** President Trump signed into law the establishment of the PPP as part of the CARES Act on March 27, 2020. The program launched just days later, on April 3, 2020, with an initial allocation of $349 billion aimed at providing forgivable loans and guarantees to small businesses impacted by the COVID-19 pandemic. Demand for the funds was intense, and the initial allocation was exhausted by April 16, marking the end of the first round of PPP. In response, Congress approved an additional $310 billion on April 24, 2020, launching the program's second round, which continued until August 8, 2020, when applications were halted again.
- **Phase 2 ("Biden").** The 2020 US presidential election occurred on November 3, 2020, resulting in Biden's election as president a few days later. The PPP received further support later in the year when, on December 27, 2020, the CAA was signed into law, granting an additional $284 billion. Under the new administration, the program reopened for a third round on January 11, 2021. Following President Biden's inauguration on January 20, the administration implemented new guidelines on February 22 to expand access to smaller and minority-owned businesses, aiming to make PPP support more equitable. The deadline for applications was initially set for March 31, 2021, but was extended to May 31. However, the PPP's funds were nearly depleted by May 4, with the program officially ending on May 31, 2021.

Loans from the initial two rounds of the PPP were issued in phase 1 and available to businesses that fit the PPP's definition of a small business, which typically required having fewer than 500 employees. The third round, initiated in phase 2, targeted businesses that had not previously received a PPP loan. Additionally, it offered "second-draw" loans to businesses that had already taken a PPP loan, had fewer than 300 employees, and could demonstrate a significant revenue decline in 2020. Notably, approximately 75% of the funding from this third round was allocated to these second-draw loans (Autor et al., 2022a).

3.2. Variables Definitions and Sources

3.2.1. PPP lending

We obtain PPP data from the SBA, which provides information on business and loan characteristics. The characteristics of the businesses that received loans under the program are their name, location, legal status (e.g., sole proprietorship, corporation), reported number of employees, and industry classification (six-digit NAICS). The loan characteristics consist of the loan amount in dollars, the date when the loan was approved, and the processing method indicating first- or second-draw loans. We use loan-level data released by the SBA in January 2022.

The original PPP data set from SBA provides a unique identifier for the originating lender, as well as the lender names, and location information. To construct our sample, we start with the whole population of PPP loans and lenders and then we exclude 21 loans for which the lender identifier is missing and 2,477 loans with approval dates outside the three rounds of PPP. Our final sample consists of 11,467,324 loans and 5,374 lenders. To identify the lender types, we manually match the PPP lenders based on their names and locations to the banks and bank holding companies (BHCs) in Call Reports and FRY-9C between 2019 and 2021. We first check whether a PPP lender can be matched to a bank included in Call Reports. If not, we then check whether the lender can be matched to a BHC covered in FRY-9C. We categorize lenders that have a match in this step as “Banks”. For unmatched ones, we categorize lenders whose names include “Credit Union”, “Farm Credit”, “Agricultural Credit”, “ACA”, “CU”, and “FCU”, as “Credit Unions”. All the rest, we categorize as “Others”.[8]

Table 1 shows the breakdown of the PPP loan sample based on the lender type. The overall PPP loan sample covers almost $800 billion in originated loans. Banks serve as the major disseminators of PPP funds: they constitute 78.99% of all PPP lenders providing 71.02% of all loans and 90.34% of the total dollar amount. Institutions other than banks and credit unions (“Others”) stepped up significantly more in the second phase of PPP in 2021.

To construct our dependent variables, we use the aggregated PPP loan dollar amount originated by a lender in a given period, as well as the number of new PPP loans originated by a lender in a given period. The dependent variables constructed are respectively labeled *Value of loans* and *Number of loans*. The baseline sample consists of lender-week observations.

3.2.2. Lender partisanship

By way of background, individuals and corporations can make contributions toward the election of a candidate in a number of ways. They can contribute directly to a candidate, to a political party, or to a political action committee (PAC). A PAC is a committee that raises and spends money to elect or

[8] The three most active PPP lenders categorized as “Others” are Prestamos CDFI, Harvest Small Business Finance LLC, and Capital Plus Financial LLC. These three financial firms extended 45.6% of the PPP loans in this category.

defeat candidates. Most PACs represent businesses (e.g., Bank of America PAC), associations (e.g., American Bankers Association PAC), or ideological causes (e.g., EMILY's List PAC). An organization's PAC solicits money from its employees or members and directs the money in the name of the PAC to candidates and political parties. Other types of PACs include "leadership PACs", where politicians raise money apart from their own campaigns to help other politicians (e.g., Majority Cmte PAC). There are limits on the amount that can be contributed. For instance, in the 2020 election cycle, an individual donor could contribute $2,800 per election to a candidate and $5,000 per year to a PAC, while a PAC could contribute up to $5,000 per election to a candidate and up to $35,500 per year to a political party committee.[9]

To measure lenders' partisanship, we obtain information on contributions by individual donors and PACs to presidential and congressional political campaigns during the 2020 election cycle.[10] Employing contributions from the 2020 cycle is consistent with our empirical strategy, and importantly allows to include small donor contributions in the analysis. Moreover, partisanship/ideology may change over time, and contributions from previous cycles may not correlate strongly with the current cycle.[11]

We source data on campaign contributions from the Center for Responsive Politics as part of its "Open Secrets" database. We capture the political support for Republicans as the ratio of campaign contributions to Republican PACs and Republican candidates to total campaign contributions. The time span is the 2020 election cycle (2019-2020). We use both campaign contributions made by individuals that are employed by the lenders and campaign contributions made by lenders as legal entities. This means that we rely on both "bottom-up" (employee-level) and "top-down" (lender-level) approaches to capture the partisanship of a lender. Most studies use only one of these approaches (e.g., Duchin et al., 2023; Kempf et al., 2023). However, there are potential concerns with each approach. On the one hand, lender-level contributions may not reflect the underlying political views of people that constitute the organization (that is, its employees and leadership), but rather strategic political decisions made by the lender. Although our preferred approach is the "bottom-up" one due to the better

[9] Following a 2010 US Court of Appeals decision, a new type of PAC was created, a "super PAC". Super PACs make no contributions to candidates or parties, but they can directly spend money on actions that specifically target an election, such as running ads or sending mail to voters. There are no restrictions on the amount, or the sources of the funds spent.

[10] We include campaign committees for all party affiliated or leadership PACs, strong ideological PACs, congressional candidate PACs, and candidate PACs for three candidates involved in the presidential election (Donald Trump, Joseph Biden, and Kamala Harris; Mike Pence did not have any candidate campaign committee registered in the 2020 election cycle).

[11] Rueda and Ruiz (2021), for example, show that, on average, donating to the winning candidate, in fact, reduces the probability of donating in the next election.

data coverage, we also use in robustness the "top-down" approach to mitigate the concerns associated with the reliance on one measure taken in isolation.

As for the "bottom-up" approach, we go to the detailed record of individual contributions data to identify lender employee partisanship. The individual contributions record for the 2020 election cycle has the advantage of including a vast number of small donors (defined as those contributing less than $200), since the major individual contribution platforms (ActBlue and WinRed) started to request all donors to disclose identities, including their employers. ActBlue was created in 2004 to help Democrats raise money and now dominates Democratic fundraising, while WinRed was launched in 2019 on the Republican side (Bouton et al., 2022; Cagé, 2024). We have over 80 million valid records of individual contributions in the 2020 cycle.[12] We run fuzzy match commands to compare employer names and lender names using various methods, including "big-ram", and "token", and manually read through all possible matches.[13] We are able to identify over half a million records where the donor's employer is a PPP lender. We drop invalid or duplicate records and contributions made to independent PACs (not political ideological) or third-party candidates. In total, we can match over 23,873 employees working for 2,548 lenders, covering 47.41% of PPP lenders (Table 1). We aggregate the contribution amounts to either Republican or Democratic candidates and leadership or ideological PACs,[14] and calculate the fraction of the contribution going to Republican candidates and PACs. Figure A1 in Appendix A shows in Panel A the distribution of employee partisanship. Most individuals demonstrate one-sided support to either Republicans or Democrats. Out of 23,873 employees, on average, one contributes $3,135 (median $500) to party PACs and candidates, out of which 45.3% (untabulated statistic) goes to Republican candidates or Republican Party PACs.

Next, we aggregate employee partisanship at the lender level. As most individuals only support one party, we consider an employee to be Republican-leaning if the fraction of her contribution amount going to Republicans is over 50%, out of the total amount going to both Republicans and Democrats. We then calculate the proportion of Republican-leaning employees in the 2020 election cycle for each PPP lender (the variable is labelled *Employee contributions to Republicans*). Figure A2 in Appendix

[12] Considering these small campaign contributions is critical to mitigate measurement concerns about data scarcity when relying on partisanship measures aggregating at the organization level contributions from employees.

[13] Many banks share similar words in their names, posing a layer of complication in identifying specific entities. Self-reported employer names by individual donors include unstandardized company names. Therefore, an individual employee may be matched to multiple banks in the same election cycle. We use location information of the donor, and the headquarters and branches of the lenders to identify the correct matches. We also manually search over 3000 potential employees' profile in LinkedIn, news releases, and lender information webpages for ambiguous matches. See Appendix B for more detail on the manual matching process.

[14] Popular party PAC recipients for employee contributions in 2020 cycle include "Republican National Cmte", "Trump Make America Great Again Cmte", and "Democratic Congressional Campaign Cmte".

A shows in Panel B the distribution of the fraction of Republican-leaning employees measured at the lender level. One can observe that a good fraction of lenders is Republican-leaning (with the measure value close to one), while a substantial number of lenders have diverse employee partisanship. On average, a lender has 67% of Republican-leaning employees out of all politically active employees. In Table 1, we report the breakdown of contributing lenders with employee contributions in the 2020 election cycle. Notably, the "bottom-up" measure of partisanship allows us to cover a majority of the PPP loan sample, utilizing over 9.1 million PPP loans (79.80% of the overall sample) and covering more than $705 billion volume (88.59% of total loan amount).

For robustness, we also aggregate employee partisanship at the lender level based on their contribution dollar amounts. We calculate each employee's contribution fraction to Republicans out of total amount to both parties and then take the average across all individual contributors employed by the same lender. We use simple average (*Employee contributions to Republicans (average value)*), or weighted average based on total dollar amount of contributions (*Employee contributions to Republicans (weighted value)*). We obtain values for these two partisanship measures that are consistent with *Employee contributions to Republicans*.

In addition to the "bottom-up" approach, we construct a measure of partisanship based on the "top-down" approach for robustness purposes; that is, we use lender contributions from the lender's corporate PAC to Republican or Democratic party leadership and ideological PACs.[15] We do not include contributions to candidates since lenders generally do not contribute directly to presidential candidates.[16] Lenders tend to contribute to congressional candidates in connection to their potential power in congressional subcommittees or in influencing policies affecting their local areas rather than based on political ideology partisanship. We manually compare all lender names (and their BHC names if applicable) to PAC names that are active in the 2020 cycle. In total, we identify 59 PPP lenders contributing via their affiliated corporate PACs to 253 various party leadership PACs during the 2020 election cycle. Although the number of matched lenders with corporate PAC contributions seems very limited (only 1.10% of all lenders in Table 1), the sample covers some of the most active PPP lenders, providing over a quarter of all PPP loans and over a third of total dollar volume. We also note from Table 1 that 55 out of 59 contributing lenders are banks. On average, a lender contributes $145,490 (median is $37,100) to party PACs, out of which 70% goes to Republican PACs. We

[15] Popular leadership PAC recipients for bank contributions in the 2020 election cycle include "Building Leadership & Inspiring New Enterprise" and "Democratic Congressional Campaign Cmte".

[16] Only one bank in our sample contributed to Trump, none to other presidential candidates, in 2020. In contrast, it is a lot more common for individuals to contribute directly to presidential candidates than their employer corporate PACs do.

calculate the proportion of the contribution dollars that go to Republican PACs out of the total amount going to either Republican or Democratic PACs as the first partisanship measure (labelled *Lender contributions to Republicans*). If the measure takes the value of 100%, the lender does not contribute to Democratic PACs at all and only to Republican PACs. Figure A2 in Appendix A shows the distribution of the measure. Notably, the distribution is similar to the distribution of employee contributions reported in Figure A1.

3.2.3. Other determinants of PPP lending

Since many other factors are likely related to PPP lending, we control for a host of other political and institutional factors, bank characteristics as well as regional characteristics in our analysis.

First, we address the potential confounding effect of lenders' political connections on their PPP lending behavior by directly proxying potential change in political connections around the 2020. We capture the exogenous change in the connected senators' political power by measuring the ascension of Senate committee chairs in the 2020 elections. We hand collect the Senate committee assignment information from Congressional Directory for the 116th and 117th Congresses and cross-check the chairs and ranking members. As Democrats gained majority control of the Senate in the 2020 elections, all Senate committee chairs were rotated from Republican Senators to Democratic Senators (one exception is the chair of Budget Committee to Independent Bernie Sanders). Following Akey et al. (2021), we include two turnover events where the previous Democratic ranking member or vice chair left the committee for the 117th Congress for relatively exogenous reasons.[17] We validify every rotation by checking news coverage and Ballotpedia. We construct a dummy variable, *Powerful politician*, indicating whether the PPP lender headquarter state is in the state whose senator took committee chair due to exogenous reasons in year 2021.

Second, we control for the political environment at the lender headquarter state. We collect the state governor party affiliations, and the number of seats held by the two parties in the state house and senate as reported by the National Conference of State Legislatures. We construct a dummy variable,

[17] The two events are as follows. First, Dick Durbin (D, Illinois) took over as the chair of the Judiciary Committee. The previous lead Democrat in the committee, Dianne Feinstein, announced that she would not to seek the chairmanship in the next Congress in November 2020 and subsequently left the Judiciary Committee in 2021. Second, Brian Schatz (D, Hawaii) became the chairman of the Committee on Indian Affairs. The previous Democratic vice chair, Tom Udall, retired in 2020 and became US Ambassador to New Zealand in 2021. We provide further details in Table A1 in Appendix A.

Republican state, indicating whether both the governor and state legislative control in the PPP lender headquarter state is Republican.[18]

Third, we control for how lenders handle the PPP applications. Borrowers may have switched to other lenders in 2021 if a lender did not treat them well in the first phase in 2020. To capture this factor, we download the consumer complaints record from the Consumer Financial Protection Bureau (CFPB) from 2020 to July 2024 and match the company names to the PPP lenders. We also search the consumers' narrative of the issues and identify those related to PPP if the narrative contains "ppp", "paycheck loan", "paycheck program", or "paycheck protection". In total we have 446 PPP-related complaints matched to 37 lenders. We thus construct a variable, *Number of PPP complaints*, being the total number of PPP-related complaints for each lender.

Fourth, we control for bank characteristics. We obtain balance sheet and income statement information from Call Reports, and matched to the previous calendar quarter. The controls include *Bank size*, *Bank ROA*, *Bank NPL*, *Bank Tier1 ratio*, and *Bank core deposit.* Naturally, the controls are only available for "bank" PPP lenders.

Last, we gather county-level data on socio-demographic conditions and on vulnerability to pandemic-induced lockdowns and social distancing, and state-level data on political conditions. To proxy for the racial and income disparity of PPP applications, we collect county-level racial, income, and population characteristics from the Census Bureau[19] and the Bureau of Economic Analysis. The dummy variable, *Minority majority county,* indicates whether the non-white population is over 50% of total population in a given county. *Income per capita* enters as the log level of per-capita income in thousands of dollars in a given county, while *Population* is the county population (also in log). Furthermore, to proxy for the resilience of an industry to a pandemic, we rely on measures of teleworkability, which are based on detailed survey information on occupations as classified by Dingel and Neiman (2020). Their indices capture the share of jobs in a given industry that can be done at home and is aggregated at the two-digit industry level using either the employment share or the wage share. Industries with a higher share of teleworkable jobs are likely to suffer less from the pandemic and from the associated social-distancing measures. To properly evaluate the teleworkability of the local workforce, we gather the employment numbers for each NAICS industry from the Bureau of Economic Analysis. *Local*

[18] For most states, the state executive and state legislative are controlled by the same party. In 20% of the cases, the state control is recorded as "divided" when the governor is not from the party that is in control of the state legislative. This variable is stable over the years 2020 and 2021 except for New Hampshire and Montana changing from Republican-controlled to divided.

[19] We use County Characteristics Resident Population Estimates, 2019 and 2021 releases, reported by US Census Bureau, Population Division.

workforce teleworkability is the weighted average of Occupational Information Network derived work-from-home score from Dingel and Neiman (2020), weighted by the number of employed under each NAICS code in a given county. And to further capture the political environment at the state level, we construct two variables measuring political ideology of the citizens and local government, sourced from Richard Fording's website (https://rcfording.wordpress.com). The variable, *State citizen liberal score*, is the revised 2016 citizen ideology series following Berry et al. (1998), while the variable, *State government liberal score*, is the 2017 state government ideology measure following Berry et al. (1998). Higher (lower) values of these political ideology variables indicate more liberal (conservative) values and positions in a state.

3.2.4. Employment

For our analysis on the real effects, we collect the weekly unemployment insurance (UI) claims from 14 state labor department websites that we supplement with data from the Opportunity Insights Economic Tracker (https://tracktherecovery.org). The country-week initial unemployment insurance claims signal increases in local unemployment in the timeliest way possible based on available statistics. The dependent variable, *UI claims rate*, is the weekly number of initial claims per 100 people in the 2019 county labor force. Initial claims data reflect the number of initial claims approved by the state. We note that the approved claims measure is distinct from the number of claims filed as it only includes claims that were ultimately accepted, not all claims submitted.

3.3. Summary Statistics

Table 2 presents the summary statistics for the key variables on PPP lending, lender partisanships, and lender and location characteristics for the main analysis. For the sake of brevity, summary statistics for all other variables are relegated to Tables A2 and A3 in Appendix A. We construct the lender-week panel data set by aggregating PPP lenders' lending activities to calendar weeks. In this baseline sample, we only keep the lenders with non-missing partisanship measures, using either "bottom-up" or "top-down" approach. We then transform the sample to a balanced panel data set by replacing the loan amount and the loan number with zeroes if the lender is not active during that week. As a result, the panel data set consists of 38 weeks (18 weeks in 2020 and 20 weeks in 2021) and 2,551 lenders. Eventually, we have 96,938 lender-week observations in the baseline sample, with an average (median) loan amount of $3.6 million ($141 thousand) and 42.9 (6) loans in a week (Table 2). On average, five employees in a lender firm make campaign contributions, and 67% of such employees support Republicans. Similarly, about 70% of total corporate PAC contributions to leadership PACs are directed towards Republicans.

4. Results

4.1. Identification Strategy

To examine the effect of lenders' partisan alignment with the administration on PPP lending, we run difference-in-differences regressions at the lender-week level:

$$Y_{it} = \beta Post_t \times \ Political\ Shock_i + \ \gamma X_{it} + \mu_i + \mu_t + \varepsilon_{it}. \quad (1)$$

We index lender by i and week by t. Y_{it} is either the total amount of loans (in log) or the total number of loans (in log) originated by lender i in week t. The data spans the two phases of the PPP (cf. subsection 3.1): from 2020W14 to 2020W32 for the first phase ("Trump") and from 2021W2 to 2021W22 for the second phase ("Biden"). $Post_t$ is a dummy variable that takes the value of one for the weeks that belong to the second phase of the PPP, and the value of zero otherwise. $Political\ Shock_i$ is a variable measuring lenders' partisanship during the 2020 presidential election. $X_{i,t}$ is a vector of lender-level control variables. μ_i and μ_t denote lender and week fixed effects, respectively. $\varepsilon_{i,t}$ is the error term. Standard errors are clustered at the lender headquarter state level and robust to heteroskedasticity. The parameter of interest is β, which captures the effect of partisan misalignment on PPP lending. If partisan *misalignment* between lenders and the administration has a positive (negative) effect on PPP lending, we expect β>0 (β<0).

The key identifying assumption in a difference-in-differences design is that of parallel trends. Identification relies on the assumption that the outcome would have behaved in a similar way across treated (Republican-leaning lenders) and control (Democratic-leaning and neutral lenders) groups absent treatment. In our setting, this translates into maintaining that the PPP lending would have evolved in a similar fashion across treated and control groups if Trump emerged as the winner of the 2020 presidential election. We provide evidence in support of this assumption in the next subsection.

4.2. Partisan Alignment and PPP Lending

Table 3 presents the difference-in-differences regression results from estimating Equation (1). The dependent variable in columns (1) and (2) is the total value of PPP lending originated in a week, while that in columns (3) and (4) is the number of PPP loans originated. We interact $Post_t$ with our main independent variable of interest, *Employee contributions to Republicans*. It captures the leaning of the lender employees towards Republican candidates relative to Democrats, ranging between zero and one; higher the value of this variable, more Republican leaning the lender is likely to be. We also interact $Post_t$ with the following controls: *Powerful politician$_i$*, *Republican state$_{i,t}$*, *Number of PPP complaints$_i$*, and *Bank size$_{it}$*. Interacting these controls allows us to account for differential effects across these bank- or bank-state characteristics.[20] For instance, there could be exclusive windows for small firms and banks that could have differential effects on small (Republican-leaning) versus large (neutral or Democratic-leaning) banks. All regressions include lender and week fixed effects, while columns (2) and (4) control for further bank characteristics.

Turning to the results, the estimated coefficient on the interaction term of interest, β, is positive and statistically significant at the 1% level in most columns. These results suggest that when the Biden administration took office following the 2020 presidential election, it was in fact the Republican-leaning lenders who engaged more actively in PPP lending during the program's second phase. The economic magnitude is also meaningful. Consider column (2). A Republican-leaning lender (with 100% Republican-leaning employees at the 75th percentile) has average weekly lending volume growth rate in the second phase 24.3% (0.3646×0.667) higher than a "neutral" bank (with the proportion to Republican at 33.3% at the 25th percentile). Considering column (4), its average number of new loans is 9.8% (0.1469×0.667) higher. Overall, these results, showing a positive relationship between partisan misalignment and PPP lending, support the idea that Republican-leaning lenders viewed the PPP's second phase as a legacy of the Trump administration. As a result, they may have increased their PPP lending to preserve or even enhance their political capital under the new administration.[21] However, these findings are inconsistent with a "contemporaneous-alignment" view typically portrayed in the literature: Democrat-leaning lenders are better aligned with the Biden administration but they do not lend as vigorously as Republican-leaning lenders despite sharing the beliefs of their co-partisans in the government.

As for the controls, they generally display the expected sign across most columns, though they are not always statistically significant at conventional levels. The interaction with the variable *Republican state* is positive in sign and statistically significant at the 5% level in columns (1) and (2) but fails to be statically significant at the 10% level in columns (3) and (4). This may suggest that there is more lending during the program's second phase in states where the lender's headquarter is controlled by

[20] In the regressions, time invariant lender-level controls are absorbed by the lender fixed effects.

[21] Another, non-mutually exclusive explanation for our findings is that the lending effects of misalignment between lenders and the government depend on who ultimately bears the credit risk. Unlike prior work, in the context of the PPP—where loans are forgivable—the government assumes the credit risk. This structure may have incentivized Republican-leaning lenders to adopt more aggressive lending strategies, potentially to deplete the resources of an ideologically distant administration through disproportionate loan issuance. Unfortunately, we are unable, with the data at hand, to disentangle and directly test this explanation.

Republicans. Lenders with a lower number of PPP-related CFPB complaints tend to lend more, although the coefficient is not stable when bank characteristics are also controlled for. Smaller banks (that are typically Republican-leaning, see below) also tend to lend more in the second phase and this relationship appears to be more stable than those with the other interaction variables. Importantly, the inclusion of these controls does not change our results on partisan misalignment.

Figure 1 plots the estimated coefficients for the value of PPP loans, which suggests that the parallel trends assumption holds.[22] The red line shows the average total loan amount each week originated by Republican-leaning lenders, with employee partisanship over the sample mean. The blue line shows the weekly loan amount by Democratic-leaning and neutral lenders, with employee partisanship equal to or less than the sample mean. Both lines evolve in parallel prior to the presidential election. While the control group (Democratic-leaning and neutral lenders) lent more than the treated group (Republican-leaning lenders) prior to the election, an increase is evident for the treated group in the weeks subsequent to the election. Republican-leaning lenders catch up and the wedge between treated (Republican-leaning lenders) and control (Democrat-leaning lenders) groups narrows.

4.3. Robustness

We first probe the robustness of our results to alternative measures of lender partisanship. Table 4 displays the results.[23] In columns (1) and (2), we present results based on lender partisanship, calculated using lender corporate PAC contributions (the "top-down approach"). The number of observations drops dramatically, as a much smaller number of lenders contribute to PACs compared to those whose employees give individual contributions (see Table 1). In columns (3) to (6), we consider the "bottom-up approach" utilizing the value of employee contributions with varying aggregation at the lender level. In all columns, we can see that our findings do not change: partisan misalignment between lenders and the administration increases PPP lending.

We also address potential concerns about the influence on PPP lending of pre-existing differences across Republican-leaning banks versus neutral or Democratic-leaning banks. In Panel A of Table A4 in Appendix A, we first test the difference in means for various bank characteristics between Republican-leaning banks and neutral or Democratic-leaning banks. The results show that Republic-leaning banks tend to be significantly smaller and report higher profits, NPLs, and core deposits. We

[22] We also arrive at a similar conclusion about parallel trends assumption if we plot the estimated coefficients for the number of PPP loans as outcome. We do not report the graph for the sake of brevity.
[23] Figure A3 shows the parallel trend graph using lender corporate PAC contributions.

then rely on a propensity score matching method based on these bank characteristics. We split the sample by the mean of partisanship measures. As banks tend to be Republican-leaning, with the median share of *Employee contribution to Republicans* at one, there are more Republican-leaning banks than Democratic-leaning and neutral banks. We keep the last quarter prior to 2020 elections and run a probit regression in this cross-sectional data set to predict the likelihood of being Republican-leaning using the bank characteristics: *Bank size, Bank ROA, Bank NPL ratio, Bank Tier1 ratio*, and *Bank core deposits*. We keep the predicted probability as the propensity score. For each Democratic-leaning/neutral bank, we find two closest Republican-leaning banks in terms of propensity score distance ($|Prob. - Prob._{match}|$). We also drop those matches where either the propensity score distance or the size distance is larger than 15%.[24] Panel B of Table A4 reports the matched sample based on employee partisanship, showing that Democratic-leaning and neutral banks and matched Republican-leaning banks are comparable with respect to all the bank characteristics we consider. Table 5 presents the results of estimating our baseline specification in this matched sample. Our results are robust: Republican-leaning lenders engaged in greater PPP lending when the Biden administration took office following the 2020 presidential election, even after conditioning on a matched sample of banks with similar pre-election characteristics.

4.4. Mechanisms and Other Explanations

Thus far, we have shown that partisan misalignment is associated with increased lending in the PPP context, contrasting with prior studies on the partisan-alignment relationship in finance. The positive effect of partisan misalignment on PPP lending that we document is consistent with the idea that Republican-leaning lenders, likely viewing the PPP's 2021 phase as a legacy policy, increased their lending to preserve political capital. Our baseline specification controls for bank characteristics, political and institutional factors, and lender and time fixed effects, addressing some concerns about confounding dynamics. However, there may be other explanations for this positive relationship, which we now explore.

4.4.1. Loan officers versus executives

One potential mechanism through which Republican-leaning lenders may have increased lending during the program's second phase is via loan officers, whose political views could have influenced

[24] Bank size distance = $|TotalAssets - TotalAssets_{match}|/TotalAssets$.

their loan approval decisions once Biden took office. Alternatively, it could involve executives who are incentivized to maintain relationships with key clients.

To test for the influence on marginal loans of loan officers, we first reconstruct our lenders' partisanship measures based on lender employee contributions by breaking them down by job titles. We utilize the occupation information from the individual contribution filings and supplement the information by manually looking up over 3,000 individuals with ambiguous occupations and employers in LinkedIn, bank information webpages, or press releases. We categorize a bank employee as an "executive" if her title or reported occupation is bank executive, chairman, president, board director, managing director, CEO, CFO, COO, CTO, CIO, or senior/executive vice president. Otherwise, we categorize the employee as "rank-and-file". Out of 23,873 contributing employees, 3,539 are bank executives working in 1,255 PPP lenders and 20,334 rank-and-file employees working in 2,098 lenders during the sample period. We recalculate the variable, *Employee contributions to Republicans*, using only the rank-and-file employees or the executives and re-estimate Equation (1).

Table 6 presents the results. We can observe from Panel A that the estimated coefficient on the variable of interest, *Rank-and-file employee contributions to Republicans*, is positive in sign and statistically significant at conventional levels in both columns. The economic effect is also in the same order of magnitude than in Table 3 (columns (2) and (4)). However, the estimated coefficient on the variable, *Executive contributions to Republicans*, is also positive in sign but is only significant at the 10% level in column (2). Although Panels A and B use different samples, judging by the estimated coefficients for the two measures of lenders' partisanship, rank-and-file employees play a more significant role in PPP lending increases. This suggests that the partisanship of those directly involved in PPP loan origination—namely, loan officers—drives our main results, consistent with the influence of partisan alignment at the operational level rather than top-down, lender-wide strategic considerations.

4.4.2. Small versus large borrowers

Chernenko et al. (2023) show that, conditional on applying to a bank, PPP loan approval odds are strongly positively correlated with firms' number of employees. Smaller firms, for example, may have gaps or mistakes in their applications, which would create scope for loan officers' preferences and decisions to affect outcomes. To investigate whether loan officers are more likely to be influenced by their personal judgement when processing loan applications, we split our loan sample based on borrower size and categorize those with less than 20 employees as "small borrowers" and the rest as "big borrowers". We then decompose our original dependent variables for loans to small/big borrowers ($-amount and number).

Table 7 presents the results. In Panel A, we find that the effects of lenders' partisanship on PPP lending to small borrowers are both statistically and economically comparable to our baseline results in Table 3, columns (2) and (4). By contrast, Panel B shows that the effects of lenders' partisanship on PPP lending to large borrowers are insignificant. Panel C reports the z-statistics comparing the estimated coefficients from Panels A and B, which are (somehow) significant in both columns. Overall, these results indicate that lenders' partisanship primarily influences marginal loans to small borrowers, consistent with the idea that such loans are more likely to be shaped by the personal discretion of loan officers. Indeed, these loans typically have less standardized and timely information available, giving officers more leeway in assessing creditworthiness.

4.4.3. First-draw versus second-draw loans

As described in Subsection 3.1, the program's second phase permitted second-draw loans. These loans are largely pre-determined, as they depend on the number of firms that received a PPP loan in the first two rounds and are eligible for a second draw. Firms qualifying for a second-draw loan are likely to be in urgent need of liquidity. Moreover, they are familiar with the process and have much of the necessary paperwork ready, having already been through it in phase 1. We therefore expect that it would be unusual for a lender to deny a valid second-draw application from a firm previously approved by the lender.

We address this possibility by decomposing the dependent variables on PPP lending depending on whether a loan is first draw or second draw. The first set of these measures only considers borrowers' first-draw loans, which include all loans from 2020 and only first-draw loans from 2021 (according to the processing method variable recorded by SBA). These measures capture lending to first-time borrowers. The second set of measures only considers borrowers' second-draw loans, which also include all loans from 2020 and only second-draw loans from 2021 (according to the processing method variable recorded by SBA). These measures capture lending to borrowers in 2020 and repeated lending to the same set of borrowers in 2021.

Table 8 contains the results. In Panel A, we find that the effects of lenders' partisanship on PPP lending to first-draw borrowers are positive in sign and statistically significant at the 1% level. This contrasts with Panel B where lenders' partisanship is not associated with PPP lending to second-draw borrowers. Panel C reports the z-statistics comparing the estimated coefficients from Panels A and B, which are highly significant in both columns. Together, these results indicate that lenders' partisanship only affects first-time borrowers, consistent with the idea that only first-draw loans are subject to the personal discretion, and thus partisanship, of loan officers, while second-draw loans are unaffected by such bias. Importantly, the significance of first-draw loans in our setting does not contradict a legacy-policy-based explanation for our results.

4.4.4. Republicans versus Democratic counties

Our findings thus far suggest that Republican-leaning lenders engaged in greater PPP lending once Biden came into power and they do so when loan officers have more discretion (small loans, second-draw loans). We now ask ourselves where do they direct credit supply? Did they lend more in Republican-leaning counties, also suggestive of legacy effects?

To answer this question, we collapse our data at the lender-county-week level and fill the missing observations with zeros to form a balanced panel data set. We use the PPP loan project county information from SBA to identify the location of the loan and match to 5-digit FIPS codes. This collapsing results in over 7 million observations. We then run the following regression:

$$Y_{ict} = \beta Post_t \times \ Political\ Shock_i + \ \gamma X_{it} + \mu_{ic} + \mu_{c\tau} + \mu_t + \varepsilon_{ict}, \tag{2}$$

where i denotes a lender, c a county, and t a week. Y_{ict} is either the total amount of loans (in log) or the total number of loans (in log) originated in county c by lender i in week t. μ_{ic} represents lender × county fixed effects and $\mu_{c\tau}$ county × PPP round fixed effects, which absorb any county-year-level socio-demographic controls. μ_t represents week fixed effects. This specification allows us to mitigate unobservable demand-side effects. The remaining variables are defined as before and the remaining Greek symbols are parameters to be estimated (the treatment effect being given by β).

In addition, we explore the location information of contributing lender employees. We identify the subset of employees from the same state of the given county as *local employees*.[25] We then calculate the fraction of such Republican-leaning local employees as the local partisanship $Political\ Shock_{ic}$ to exploit within-lender variations of employees' partisanship. For local employees' partisanship, we run the following regression:

[25] Unfortunately, we lack county-level information for individual donors from the FEC data, and the mapping between cities/zip codes and counties is not one-to-one. Bank employees may travel to neighboring cities for work or handle applications from other cities. Therefore, we classify employees within the same state as *local employees*.

$$Y_{ict} = \beta Post_t \times Political\ Shock_{ic} + \gamma X_{it} + \mu_{ic} + \mu_{c\tau} + \mu_t + \varepsilon_{ict}, \tag{3}$$

where subscript, variables, parameters are defined similarly as above.

Table 9 presents the results of estimating Equation (2) in columns (1) to (4) and Equation (3) in columns (5) to (8). First, we can observe from columns (1)-(4) that our main findings carry through in the county-level analysis. Using the estimated coefficient in column (2), a Republican-leaning lender (with 100% Republican leaning employees at the 75th percentile) has average weekly lending volume growth rate in the second phase 5.9% (0.0801×0.733) higher than a "neutral" bank (with 26.7% Republican-leaning employees at the 25th percentile) across counties. Its growth rate in average number of new loans is 1% (0.0147×0.733) higher across counties (column (4)). Second, in columns (5)-(8), we find that local employees' partisanship from the same state on the county-level PPP lending has a weaker effect but still comparable to that of all employees.

We further explore this idea by looking in Table 10 at the cross-sectional heterogeneity of the partisanship-PPP lending relationship. In Panel A, we focus on county-level socio-demographic characteristics, while in Panel B we consider state-level characteristics of the political environment. In Panel A, the estimated coefficients on the triple interaction terms are negative in sign and statistically significant at the 1% level in all columns. These results indicate that Republican-leaning lenders expanded their PPP lending more significantly during the program's second phase, particularly in counties with a larger white population, lower personal income per capita, and a workforce less suited to teleworking. These counties often align with Republican strongholds, which supports the notion that partisanship influenced PPP lending patterns—a legacy reflecting the policies of the Trump administration. In Panel B, the estimated coefficients on the triple interaction terms display the expected signs and are statistically significant at the 1% level across all columns. The results suggest that, irrespective of the measures used across columns, Republican-leaning lenders primarily directed loans to borrowers in Republican states. Again, this is consistent with a legacy-policy view.

4.5. Real and Aggregate Effects of Partisan Misalignment

4.5.1. Employment effects at the county level

The PPP was intended to support small businesses and their employees. Our findings show that partisan misalignment increased loan origination during the PPP's second phase. But what are the real effects of this misalignment? To what extent did it help save more jobs? We address these questions by estimating the additional number of workers who would rely on unemployment insurance (UI) in the absence of partisan misalignment during the PPP's second phase.

With county-level weekly UI data, we run the following regression:

$$Y_{ct} = \beta Post_t \times \ Political\ Shock_{c(t)} + \gamma X_{ct} + \mu_c + \mu_t + \varepsilon_{ct}, \qquad (4)$$

where subscripts, variables, parameters are defined similarly as before. The dependent variable, Y_{ct}, is the weekly number of UI initial claims rate (labeled as *UI claims rate)*. It is also important to emphasize that $Political\ Shock_c$ is constructed at the county level. Specifically, we focus on the employee contributions of lenders originating PPP loans in each county. For each county *c*, we calculate the weighted average of these lenders' partisanship, using their PPP lending activity in the county as weights. For a given lender *i*, let $Political\ Shock_i$ represents its (local) employees' partisanship, and $TotalLoan_{ic}$ represents the total dollar value of PPP loans that lender *i* originated in county *c*. The total PPP loans originated in county *c* is then given by $TotalLoan_c = \sum_i TotalLoan_{ic}$. We average all active lenders' partisanship in each county as follows: $Political\ Shock_c = \frac{\sum_i (PoliticalShock_i \times TotalLoan_{ic})}{TotalLoan_c}$. Essentially, $Political\ Shock_c$ measures the average partisanship of PPP lenders active in each county, weighted by their aggregated PPP loan volumes in the county. This measure, however, is time invariant as it calculates a weighted average of the partisanship of all PPP lenders that have ever issued loans in the county, assigning higher weights to lenders with a larger market share in PPP lending. To capture temporal changes, we also construct a measure using the moving average of the partisanship of PPP lenders who issued loans in the past four weeks within a given county. Let $LoanValue_{ics}$ denotes the total PPP lending dollar value originated by lender *i* in county *c* during week *s*. For each lender *i*, the total PPP lending dollar value over the past four weeks before week *t* in county *c* is calculated as: $TotalLoan_{ict} = \sum_{s=t-1}^{t-4} LoanValue_{ics}$. This allows us to construct a time-varying county-level partisanship measure for PPP lenders, capturing local contributions by lender employees to Republicans, as a moving average: $Political\ Shock_{ct} = \frac{\sum_i (PoliticalShock_i \times TotalLoan_{ict})}{TotalLoan_{ct}}$.

Table 11 shows the results of the effects of partisan misalignment on UI claims rate, finding that partisan misalignment is associated with lower unemployment. In column (1), the estimated coefficient on the interaction term of interest is negative in sign and statistically significant at conventional levels. A county with Republican-leaning lenders (with average 78.4% Republican-leaning employees at the 75th percentile) experienced a reduction in average weekly UI rate from 2020 to 2021 of 0.27

(0.9839×0.279) larger than a "neutral" bank (with 50.5% Republican leaning employees at the 25th percentile). This is economically meaningful as it represents 31.5% of the sample mean of UI rate. In column (2), we obtain results consistent with those in column (1) when we calculate county-level lender partisanship using only local employees. In column (3), we use the moving average measure of lender partisanship. The estimated coefficient on the interaction term of interest is again negative in sign and statistically significant at conventional levels. The reduction in UI rate in counties with Republican-leaning lenders (79.3% at the 75th percentile) is 0.2 (0.5824×0.345) larger than a "neutral" bank (44.8% at the 25th percentile), which is meaningful as it corresponds to 23.2% of the sample mean. In last column, we include county × PPP round fixed effects to absorb potential county-level demand shocks. The result remains largely the same as in column (3). Overall, this evidence using county-level weekly UI data suggests that partisan misalignment is associated with higher PPP payroll coverage for small businesses. This is remarkable because it underscores that partisan misalignment has real effects that extend beyond its direct effects on PPP loan origination.

4.5.2. PPP lending effects at the county level

To assess the aggregate effects of our results on PPP loan origination, we now examine whether the effect of misalignment aggregates at the county level. Table 12 presents the results, for which the dependent variable is the aggregate PPP lending within a county in each week. Our measure of lender partisanship at the county-level is the time-invariant variable, $Political\ Shock_c$.[26] In column (1), a county with Republican-leaning lenders (with average 78.4% Republican-leaning employees at the 75th percentile) experience a growth rate in weekly PPP lending of 32.26% (1.1563×0.279) higher than a "neutral" lender (with 50.5% Republican leaning employees at the 25th percentile). For the number of PPP loans originated in column (2), the effect is 12%. In the remaining columns, we show that the results are similar if we only consider local employees to calculate PPP lender partisanship at the county level. These results are important because they demonstrate that lenders whose partisanship became misaligned with that of the administration during the PPP's second phase engaged more actively in the program, with these effects being tangible at the county level.

5. Conclusion

Initially authorized for $659 billion in business loans, the PPP ultimately grew into an $800-billion program, an unprecedented scale in US history (Autor et al., 2022a). The program has faced significant

[26] We do not use the moving average measure of lender partisanship as it uses the lagged dependent variable in the calculation.

criticism regarding the allocation of funds. This paper represents the first systematic attempt to examine whether partisan alignment influenced the allocation of PPP aid, a crucial issue in the politically polarized context of its implementation.

Our findings show that partisan alignment significantly impacts the allocation of PPP loans, revealing how political affiliations within financial institutions shape lending decisions in government aid programs. Specifically, we exploit the staggered rollout of the program to demonstrate that partisan misalignment between lenders and the administration resulted in increased loan origination during the PPP's second phase, particularly benefiting small and first-time PPP borrowers, and those in Republican-leaning areas. The effects of partisan misalignment at the bank level are also evident at the aggregate (county) level. We further show the real effects: partisan misalignment is associated with higher payroll coverage for small businesses through PPP loans.

Taken together, our results suggest that politically misaligned lenders may respond to legacy programs of a former administration with heightened engagement under a new administration, potentially to maintain or bolster their political capital. A complementary explanation, which we cannot fully disentangle, relates to who ultimately bears the credit risk. Since PPP loans are forgivable, the administration in charge bears the cost of defaults, allowing misaligned (Republican-leaning) lenders to adopt more aggressive lending strategies. These findings paint a rather "benign" picture of political polarization in finance, challenging the notion that partisan-misaligned behavior in financial institutions always leads to negative outcomes. Therefore, they carry significant implications for the effectiveness of government aid programs and provide new insights into the intersection of politics and finance, particularly regarding the partisan-alignment phenomenon.

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Figure 1: Parallel Trends

The figure shows the parallel trends for the PPP lending volume ($-amount, log) around the 2020 election cycle. Red line depicts the average total loan amount each week originated by Republican-leaning lenders, with employee partisanship (*Employee contributions to Republicans)* over sample mean. Blue line shows the weekly loan amount by Democratic-leaning and neutral lenders, with *employee partisanship* equal to or less than sample mean.

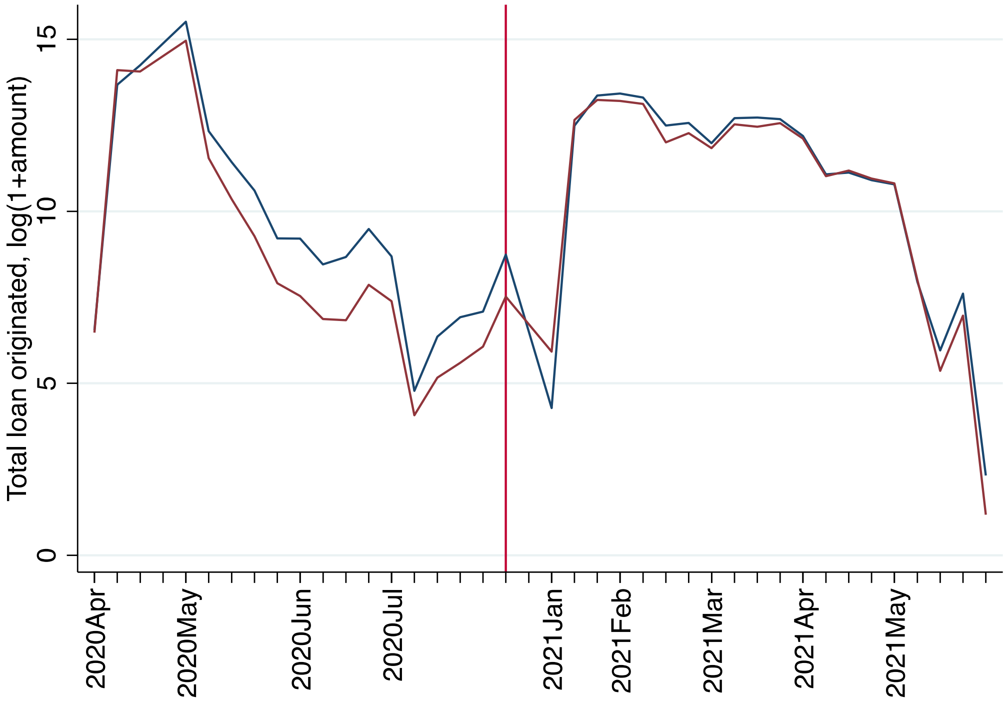


Table 1: PPP Lender Sample

The table reports the total numbers, the total loan amounts, and the total lender counts of PPP loans covered in different samples. All sample is the original PPP loan sample obtained from SBA website, dropping loans with missing lender identifiers or originating dates after the PPP end date. Year 2020/2021 sample is the loans originated in the first phase of PPP (in 2020/2021). *With employee contributions* sample includes those where the lenders' employees made individual contributions to Republican or Democratic presidential and congressional candidates, as well as party PACs in the 2020 election cycle. *With corporate PAC contributions* sample is the sample covered by lenders with valid campaign contributions from their affiliated corporate PACs to Republican or Democratic party PACs in the 2020 election cycle. The coverages by these two samples, in terms of the number of loans, total loan amounts, and covered lender, relative to the all sample are reported in the percentage's column. The statistics for three sub samples, Banks, Credit Unions, and Others, are also included in the subsequent rows. These three subsamples include PPP loans where the lenders are banks, credit unions, and other financial firms, respectively.

	Year	Number of PPP loans		Total loan amount ($m)		Number of PPP lenders	
All		11,467,324	100.00%	796,496.56	100.00%	5,374	100.00%
	2020	5,136,366		525,765.08		5,298	
	2021	6,330,958		270,731.48		5,153	
	With employee contributions	9,151,484	79.80%	705,591.09	88.59%	2,548	47.41%
	With corporate PAC contributions	2,903,213	25.32%	268,793.48	33.75%	59	1.10%
Banks		8,144,108	71.02%	719,592.16	90.34%	4,245	78.99%
	2020	4,600,836		501,578.65		4,212	
	2021	3,543,272		218,013.51		4,148	
	With employee contributions	7,240,105	63.14%	662,723.55	83.20%	2,155	40.10%
	With corporate PAC contributions	2,703,594	23.58%	264,790.28	33.24%	55	1.02%
Credit Unions		405,326	3.53%	16,598.76	2.08%	958	17.83%
	2020	212,931		10,511.75		940	
	2021	192,395		6,087.01		851	
	With employee contributions	239,618	2.09%	9,955.48	1.25%	338	6.29%
	With corporate PAC contributions	1232	0.01%	47.89	0.01%	2	0.04%
Others		2,917,890	25.45%	60,305.64	7.57%	171	3.18%
	2020	322,599		13,674.68		146	
	2021	2,595,291		46,630.96		154	
	With employee contributions	1,671,761	14.58%	32,912.06	4.13%	55	1.02%
	With corporate PAC contributions	198,387	1.73%	3,955.32	0.50%	2	0.04%

Table 2: Summary Statistics

The table presents summary statistics for the key variables of the baseline panel sample (lender-week level) except for the county-level variables. The sample only keeps PPP lenders with PAC or employee contributions in the 2020 election cycle. All variables are winsorized at the 1st and 99th percentiles. *Value of loans* is the aggregated loan dollar amount originated in a calendar week by a given lender. *Number of loans* is the number of new PPP loans originated in a week by a given lender. *Value of loans (log 1+)* is the natural logarithm of *loan amount* plus one. *Number of loans (log 1+)* is the natural logarithm of number of new loans plus one. *First draw loans* are the PPP loans extended to new borrowers in 2020 or in 2021 with the processing method identified as "PPP". *Second draw loans* include PPP loans extended in 2020 and those to previous borrowers in 2021 with the processing method identified as "PPS". *Loans to small (big) borrowers* are the PPP loans extended to borrowers with reported number of employees under (at least) 20. *Employee contributions to Republicans* is the fraction of employees contributing more than half to Republican PACs or candidates in a given lender during the 2020 election cycle. *Employee contributions to Republicans (average value)* is the simple average for a given lender of each employee's contribution fraction to Republican candidates and PACs out of to either party (fraction of total). *Employee contributions to Republicans (weighted value)* is the weighted average for a given lender of each employee's contribution fraction to Republican candidates and PACs out of to either party, weighted by individual's total contribution amount. *Number of contributing employees* is the number of contributing employees in the 2020 election cycle in a lender. *Lender contributions to Republicans* is the fraction of total contributions made from a lender's corporate PAC to Republican leadership PACs or party PACs out of the total contributions to either party in the 2020 election cycle. *Powerful politician* is the dummy indicator on whether the lender headquarter state is either Illinois or Hawaii. *Republican state* is a dummy variable that takes the value of one if the lender headquarter is in a state controlled by Republican in 2020, zero otherwise. *Number of PPP complaints in CFPB* is the number of consumer complaints mentioning PPP since 2020 from CFPB. *Number of PPP* complaints (log 1+) is the natural logarithm of number of PPP complaints plus one. *Rank-and-file employee (Executive) contributions to Republicans (number)* is the fraction of rank-and-file employees (executives) contributing more than half to Republican PACs or candidates in a given lender during the 2020 election cycle. *Number of contributing rank-and-file employees (executives)* is the number of contributing rank-and-file employees (executives) in the 2020 election cycle in a lender. *Bank size* is the natural logarithm of one plus bank's total assets in the previous quarter. *Bank ROA (%)* is quarterly net income×4/total assets×100, lagged one quarter. *Bank NPL (%)* is loans past due 90 days or more and nonaccruals over total loans ×100, lagged one quarter. *Bank Tier1 (%)* is tier one capital over total loans ×100, lagged one quarter. *Bank core deposits (%)* is the sum of transactions deposits and all other savings deposits that are included in total non-transaction accounts, excluding MMDAs, over total deposits ×100, lagged one quarter. The county-level characteristics are at the county-week level. *Local workforce teleworkability* is the weighted average of Occupational Information Network derived work-from-home score from Dingel and Neiman (2020), weighted by the number of employments under each NAICS code for a given county. *Minority majority county* is a dummy variable that takes the value of one if the non-white population in a given county is over 50% of total population, zero otherwise. *Income per capita* is county personal income per capita in $thousands. *Population (log)* is the natural logarithm of the county population. *UI claims rate* is the weekly number of unemployment insurance initial claims at the county level per 100 people in the 2019 labor force from Opportunity Insights Economic Tracker.

	Obs.	Mean	S.D.	Perc. 25	Median	Perc. 75
PPP lending						
Value of loans ($thousand)	96938	3646.189	13849.381	3.250	141.119	1033.095
Number of loans	96938	42.879	133.170	1	6	25
Value of loans (log 1+)	96938	9.784	5.880	8.087	11.857	13.848
Number of loans (log 1+)	96938	2.067	1.740	0.693	1.946	3.258
Lender Partisanship						
Employee contributions to Republicans	96824	0.669	0.398	0.333	1	1
Employee contributions to Republicans (average value)	96824	0.669	0.396	0.333	0.957	1
Employee contributions to Republicans (weighted value)	96824	0.679	0.419	0.200	0.998	1
Number of contributing employees	96824	5.002	14.554	1	2	3
Lender contributions to Republicans	2242	0.700	0.346	0.432	0.912	1
Other determinants of PPP lending						
Powerful politician	96938	0.056	0.230			
Republican state	96900	0.458	0.498			
Number of PPP complaints in CFPB	96938	0.014	0.116	0	0	0
Number of PPP complaints (log 1+)	96938	0.010	0.081	0	0	0
Bank size (log 1+)	81630	13.412	1.464	12.432	13.203	14.131
Bank ROA (%)	81630	2.190	1.988	0.922	1.542	3.234
Bank NPL (%)	81529	0.807	0.984	0.189	0.503	1.021
Bank Tier1 ratio (%)	81630	10.252	2.507	8.666	9.710	11.136
Bank core deposits (%)	81579	61.683	18.541	50.773	64.937	75.162
Local workforce teleworkability	117116	0.271	0.051	0.242	0.270	0.298
Minority majority county	119016	0.057	0.232			
Income per capita ($thousand)	117116	51.429	14.442	43.031	48.659	56.313
Population (log)	119016	10.274	1.482	9.293	10.158	11.133
Employment						
UI claims rate	48093	0.861	0.981	0.288	0.502	0.970

Table 3: Partisan Alignment and PPP Lending

This table documents the effects of lenders' partisanship on PPP lending. The difference-in-differences regression is specified in Equation (1) in the lender-week panel data set. The dependent variables are *Value of loans (log 1+)* and *Number of loans (log 1+)*. The measure for lenders' partisanship is based on employee contributions to Republican (fraction of Republican-leaning employees). All variables are defined in the note of Table 2. *t*-statistics are in the parentheses. Robust standard errors are clustered at the lender headquarter state level. Variables are winsorized at the 1st and 99th percentiles. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	Value of loans		Number of loans	
Post × Employee contributions to Republicans	0.8130***	0.3646**	0.2407***	0.1469***
	(3.9192)	(2.0272)	(4.2029)	(3.0268)
Post × Powerful politician	0.0760	-0.1712	0.0336	-0.0127
	(0.4882)	(-0.9263)	(0.6274)	(-0.2259)
Republican state	-0.8615	-1.1012*	-0.1759	-0.2372
	(-1.4162)	(-1.9524)	(-0.9451)	(-1.2813)
Post × Republican state	0.4582**	0.3634**	0.1108	0.1054
	(2.2804)	(2.0721)	(1.3866)	(1.4608)
Post × Number of PPP complaints	-1.8228***	1.1696*	-0.4757**	-0.1519
	(-3.4060)	(1.7896)	(-2.3330)	(-0.6369)
Bank size		-1.6374***		-0.6567***
		(-3.4237)		(-4.2262)
Post × Bank size		-0.5168***		-0.0636***
		(-6.3490)		(-2.9121)
Bank ROA		0.0329		0.0219***
		(1.1992)		(2.8348)
Bank NPL		-0.0300		-0.0345*
		(-0.4159)		(-1.8872)
Bank tier1 ratio		-0.1004*		-0.0418***
		(-2.0070)		(-2.9161)
Bank core deposits		-0.0064		-0.0019
		(-1.0750)		(-1.3516)
Lender FE	Y	Y	Y	Y
Week FE	Y	Y	Y	Y
Adj. R-sq	0.546	0.564	0.705	0.733
N	96786	81414	96786	81414

Table 4: Robustness: Alternative Measures of Partisanship

This table documents the effects of partisanship on PPP lending using alternative measures of partisanship based on bank corporate PAC contributions and employee contributions (that is, different aggregation of employee partisanship to the lender level). The difference-in-differences regression is specified in Equation (1). The dependent variables are *Value of loans (log 1+)* and *Number of loans (log 1+)*. All variables are defined in the note of Table 2. *t*-statistics are in the parentheses. Robust standard errors are clustered at the lender state level. Variables are winsorized at the 1st and 99th percentiles. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Value of loans	(2) Number of loans	(3) Value of loans	(4) Number of loans	(5) Value of loans	(6) Number of loans
Post × Lender contributions to Republicans	2.3037*	1.0848***				
	(1.8271)	(3.4297)				
Post × Employee contributions to Republicans (average value)			0.3603*	0.1449***		
			(1.9844)	(2.9760)		
Post × Employee contributions to Republicans (weighted value)					0.3678**	0.1392***
					(2.0515)	(2.9632)
Post × Powerful politician	1.5937	0.4065	-0.1683	-0.0116	-0.1696	-0.0120
	(1.4197)	(1.1421)	(-0.9044)	(-0.2049)	(-0.9081)	(-0.2113)
Republican state			-1.1021*	-0.2376	-1.1009*	-0.2392
			(-1.9527)	(-1.2821)	(-1.9202)	(-1.2632)
Post × Republican state	-0.0167	-0.0392	0.3635**	0.1055	0.3611**	0.1059
	(-0.0181)	(-0.1392)	(2.0703)	(1.4586)	(2.0267)	(1.4651)
Post × Number of PPP complaints	-1.0573	-1.2093**	1.1693*	-0.1520	1.1563*	-0.1576
	(-0.5738)	(-2.4430)	(1.7895)	(-0.6376)	(1.7629)	(-0.6616)
Bank size	-2.9914	-2.3955	-1.6383***	-0.6571***	-1.6319***	-0.6552***
	(-0.5661)	(-1.6129)	(-3.4247)	(-4.2277)	(-3.3948)	(-4.2028)
Post × Bank size	-0.3281	-0.0162	-0.5170***	-0.0637***	-0.5194***	-0.0649***
	(-1.3007)	(-0.1861)	(-6.3552)	(-2.9171)	(-6.3678)	(-2.9660)
Bank ROA	-0.2896	-0.1709*	0.0329	0.0219***	0.0322	0.0216***
	(-1.2329)	(-2.0245)	(1.2001)	(2.8351)	(1.1725)	(2.7954)
Bank NPL	4.1368**	0.8805**	-0.0301	-0.0345*	-0.0303	-0.0348*
	(2.7453)	(2.3253)	(-0.4181)	(-1.8915)	(-0.4229)	(-1.9137)
Bank tier1 ratio	-0.0651	-0.1190	-0.1006**	-0.0419***	-0.1005*	-0.0418***
	(-0.0755)	(-0.5318)	(-2.0113)	(-2.9238)	(-1.9906)	(-2.8927)
Bank core deposits	-0.0507	-0.0160*	-0.0064	-0.0019	-0.0065	-0.0019
	(-1.5765)	(-1.9826)	(-1.0770)	(-1.3538)	(-1.0790)	(-1.3557)
Lender FE	Y	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y	Y
Adj. R-sq	0.610	0.765	0.564	0.732	0.564	0.733
N	2052	2052	81414	81414	81414	81414

Table 5: Robustness: Matched Sample

This table performs the same tests as in columns 2 and 4 in Table 3, in a matched sample. The difference-in-differences regression is specified in Equation (1) in the matched lender-week panel data set. We use a propensity score method to find up to two matched Republican-leaning lenders for each Democratic-leaning & neutral lender. *Republican-leaning lender*s have *employee contributions to Republican* higher than sample mean, and the rest are Democratic-leaning and neutral lenders. The propensity score is the estimated probability of a probit model regressing *Republican-leaning lender* on *bank size, ROA, NPL, tier1 ratio, and core deposits* in the last quarter of the second round of PPP in 2020. The dependent variables are *Value of loans (log 1+)* and *Number of loans (log 1+)*. All variables are defined in the note of Table 2. *t*-statistics are in the parentheses. Robust standard errors are clustered at the lender state level. Variables are winsorized at the 1st and 99th percentiles. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Value of loans	(2) Number of loans
Post × Employee contributions to Republicans	0.3967*	0.1237**
	(1.8136)	(2.1452)
Post × Powerful politician	-0.3876**	-0.0949*
	(-2.2128)	(-1.8305)
Republican state	-0.6778	-0.1600
	(-1.0917)	(-0.8454)
Post × Republican state	0.1928	0.1051
	(0.8104)	(1.3220)
Post × Number of PPP complaints	1.2980	0.0047
	(1.3434)	(0.0123)
Bank size	-1.8822	-0.8018**
	(-1.4899)	(-2.2868)
Post × Bank size	-0.5967***	-0.0887**
	(-5.7073)	(-2.5992)
Bank ROA	0.0692	0.0395***
	(1.6337)	(3.3425)
Bank NPL	0.0774	-0.0144
	(0.7118)	(-0.5027)
Bank tier1 ratio	-0.1248	-0.0643**
	(-1.2735)	(-2.2358)
Bank core deposits	-0.0038	0.0002
	(-0.5251)	(0.1005)
Lender FE	Y	Y
Week FE	Y	Y
Adj. R-sq	0.575	0.737
N	91257	91257

Table 6: Loan Officers versus Executives

This table documents the effects of partisanship based on different set of employees on PPP lending. The difference-in-differences regression is specified in Equation (1). The dependent variables are *Value of loans (log 1+)* and *Number of loans (log 1+)*. In Panel A, the measure for partisanship is the fraction of Republican-leaning *rank-and-file* employees out of all contributing rank-and-file employees. In Panel B, the measure for partisanship is the fraction of Republican-leaning lender executives. Executives include employees whose titles are C*X*Os, president, chairman, board director, managing director, executive, or senior/executive vice president; all the rest are rank-and-file employees**.** The set of control variables include all control variables in column 2 of Table 3**.** All variables are defined in the notes of Tables 2 and A2. *t*-statistics are in the parentheses. Robust standard errors are clustered at the lender state level. Variables are winsorized at the 1st and 99th percentiles. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
Panel A: Rank and file employees	Value of loans	Number of loans
Post × Rank-and-file employee contributions to Republicans	0.2917*	0.1293***
	(1.7345)	(2.7853)
Controls	Y	Y
Lender FE	Y	Y
Week FE	Y	Y
Adj. R-sq	0.567	0.735
N	67911	67911
Panel B: Executives	Value of loans	Number of loans
Post × Executive contributions to Republicans	0.2053	0.0996*
	(1.0229)	(1.7457)
Controls	Y	Y
Lender FE	Y	Y
Week FE	Y	Y
Adj. R-sq	0.575	0.746
N	39837	39837

Table 7: Small versus Large Borrowers

This table documents the effects of partisanship on PPP lending to small and big borrowers. The difference-in-differences regression is specified in Equation (1). In Panel A, the dependent variables are *Value of loans (log 1+)* and *Number of loans (log 1+)* but only restricted to loans *to small borrowers* with less than 20 employees. In Panel B, the dependent variables are only including loans *to big borrowers* with at least 20 employees. The measure for partisanship is based on employee contributions (fraction of Republican-leaning employees). The set of control variables include all control variables in column 2 of Table 3. All variables are defined in the notes of Tables 2 and A2. *t*-statistics are in the parentheses. Robust standard errors are clustered at the lender state level. Variables are winsorized at the 1st and 99th percentiles. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. In Panel C, z-statistics are the difference of the coefficients in the same column from Panel A and B, over the square root of the sum of the variances of the two estimated coefficients.

	(1)	(2)
Panel A: to small borrowers	Value of loans	Number of loans
Post × Employee contributions to Republicans	0.3677**	0.1491***
	(2.1217)	(3.1071)
Controls	Y	Y
Lender FE	Y	Y
Week FE	Y	Y
Adj. R-sq	0.558	0.728
N	81414	81414
Panel B: to big borrowers	Value of loans	Number of loans
Post × Employee contributions to Republicans	0.0204	-0.0156
	(0.1592)	(-0.9819)
Controls	Y	Y
Lender FE	Y	Y
Week FE	Y	Y
Adj. R-sq	0.534	0.651
N	81414	81414
Panel C: Compare coefficients in A and B		
Z-stat.	1.612	3.258
P value	0.107	0.001

Table 8: First-Draw versus Second-Draw Loans

This table documents the effects of partisanship on PPP lending in two different batches. The difference-in-differences regression is specified in Equation (1). In Panel A, the dependent variables are *Value of loans (log 1+)* and *Number of loans (log 1+)* but only restricted to *first-draw loans*, including all loans originated in 2020 and first-draw loans only in 2021. In Panel B, the dependent variables are only including *second-draw loans*, including all loans originated in 2020 and second-draw loans only in 2021. The measure for partisanship is based on employee contributions (fraction of Republican-leaning employees). The set of control variables include all control variables in column 2 of Table 3. All variables are defined in the notes of Tables 2 and A2. *t*-statistics are in the parentheses. Robust standard errors are clustered at the lender state level. In Panel C, z-statistics are the difference of the coefficients in the same column from Panel A and B, over the square root of the sum of the variances of the two estimated coefficients. Variables are winsorized at the 1st and 99th percentiles. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
Panel A: First-draw loans	Value of loans	Number of loans
Post ×Employee contributions to Republicans	0.7581***	0.2453***
	(3.3974)	(3.9382)
Controls	Y	Y
Lender FE	Y	Y
Week FE	Y	Y
Adj. R-sq	0.521	0.691
N	81414	81414
Panel B: Second-draw loans	Value of loans	Number of loans
Post ×Employee contributions to Republicans	0.1771	-0.0051
	(1.0562)	(-0.1382)
Controls	Y	Y
Lender FE	Y	Y
Week FE	Y	Y
Adj. R-sq	0.548	0.728
N	81414	81414
Panel C: Compare A and B		
Z-stat.	2.082	3.458
P value	0.037	<0.001

Table 9: Republicans versus Democratic Counties

This table documents the effects of partisanship on PPP lending at the lender-county level. The difference-in-differences regression is specified in Equations (2) and (3) in the lender-county-week panel data set. The dependent variables are *Value of loans (log 1+)* and *Number of loans (log 1+)*. The measure for partisanship is based on employee contributions (fraction of Republican-leaning employees) in columns 1 to 4; and fraction of Republican-leaning employees in the same state of the given county in columns 5 to 8. All variables are defined in the note of Table A5. *t*-statistics are in the parentheses. Robust standard errors are clustered at the lender state level. Variables are winsorized at the 1st and 99th percentiles. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Value of loans		Number of loans		Value of loans		Number of loans	
Post × Employee contributions to Republicans	0.5479***	0.0801**	0.0720***	0.0147***				
	(18.3709)	(2.5570)	(20.1410)	(3.9262)				
Post × Local employee contributions to Republicans					0.2770***	0.0617	0.0355***	0.0107*
					(4.2960)	(1.3803)	(3.8602)	(1.7283)
Post × Powerful politician (headquarter state)	-0.3205***	-0.2194**	-0.0436***	-0.0259**	-0.1479	-0.2362	-0.0165	-0.0200
	(-3.6003)	(-2.4660)	(-4.4683)	(-2.5424)	(-0.6401)	(-1.2216)	(-0.6353)	(-0.9511)
Republican state (headquarter)	0.1019	0.1474	0.0152	0.0222	0.1502	0.0872	0.0224	0.0116
	(0.5983)	(0.9675)	(0.6594)	(1.0864)	(0.5750)	(0.3168)	(0.4995)	(0.2383)
Post × Republican state (headquarter)	-0.3017***	-0.2126***	-0.0419***	-0.0283***	-0.1206	-0.0977	-0.0191	-0.0099
	(-9.1133)	(-6.7804)	(-8.2937)	(-6.6199)	(-1.2395)	(-1.5419)	(-1.3716)	(-1.1652)
Post × Number of PPP complaints	-0.0021	0.1652***	-0.0016	0.0199***	-0.0636***	0.0044	-0.0088***	0.0024
	(-0.1961)	(8.2595)	(-0.8880)	(7.1442)	(-4.0095)	(0.1726)	(-3.3552)	(0.6710)
Bank size		0.4869***		0.0686***		-0.3234*		-0.0360
		(7.4635)		(7.7426)		(-1.6861)		(-1.2682)
Post × Bank size		-0.1027***		-0.0126***		-0.0614***		-0.0087***
		(-12.0179)		(-12.0595)		(-4.3456)		(-4.7321)
Bank ROA		-0.0597***		-0.0078***		-0.0508***		-0.0063***
		(-9.3516)		(-7.7539)		(-3.6721)		(-2.7799)
Bank NPL		0.0892***		0.0107***		0.0050		-0.0013
		(4.7123)		(4.1378)		(0.1706)		(-0.3662)
Bank tier1 ratio		0.1185***		0.0171***		-0.0108		-0.0018
		(18.2131)		(15.3725)		(-0.3702)		(-0.3914)
Bank core deposits		-0.0022***		-0.0004***		-0.0021*		-0.0005**
		(-2.9289)		(-3.7399)		(-1.7074)		(-2.4249)
Lender × county FE	Y	Y	Y	Y	Y	Y	Y	Y
County × PPP round FE	Y	Y	Y	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y	Y	Y	Y
Adj. R-sq	0.375	0.413	0.478	0.527	0.459	0.474	0.556	0.570
N	7373900	6048597	7373900	6048597	3119610	2790221	3119610	2790221

Table 10: Republicans versus Democratic Counties: Further Cross-Sectional Heterogeneity

This table documents the effects of partisanship on PPP lending at the lender-county level. The dependent variables are *Value of loans (log 1+)* and *Number of loans (log 1+)*. The measure for partisanship is based on employee contributions (fraction of Republican-leaning employees). In Panel A, the interaction terms are further interacted with three county-level demographic characteristics. *Minority majority county* is a dummy variable that takes the value of one if the non-white population is over 50% of total population in 2019, zero otherwise. *Income per capital* is county income per capita in $thousands in 2019. *Local workforce teleworkability* is the weighted average of Occupational Information Network derived work-from-home score from Dingel and Neiman (2020), weighted by the number of employments under each NAICS code for a given county in 2019. Panel B shows the cross-sectional variations across the ideological bias in the local state. *Republican state* is a dummy variable that takes the value of one if the given county is in a state controlled by Republican in 2020, zero otherwise. *State citizen liberal score* is the revised 2016 citizen ideology series following Berry et al. (1998). *State government liberal score* is the 2017 state government ideology measure following Berry et al. (1998). All other variables are defined in the note of Table A5. *t*-statistics are in the parentheses. Robust standard errors are clustered at the lender state level. Variables are winsorized at the 1st and 99th percentiles. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Interactions with socio-demographic characteristics and teleworkability

	(1) Value of loans	(2) Number of loans	(3) Value of loans	(4) Number of loans	(5) Value of loans	(6) Number of loans
Post × Employee contributions to Republicans	0.0889***	0.0162***	0.4202***	0.0564***	0.8009***	0.1051***
	(2.7242)	(4.2212)	(6.7904)	(6.1195)	(9.6122)	(8.1112)
Post × Employee contributions to Republicans × Minority majority county	-0.1237***	-0.0216***				
	(-2.7955)	(-4.1976)				
Post × Employee contributions to Republicans × Income per capita			-0.0065***	-0.0008***		
			(-7.0339)	(-5.4295)		
Post × Employee contributions to Republicans × Local workforce teleworkability					-2.3230***	-0.2909***
					(-10.0989)	(-7.6687)
Controls	Y	Y	Y	Y	Y	Y
Lender × county FE	Y	Y	Y	Y	Y	Y
County × PPP Round FE	Y	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y	Y
Adj. R-sq	0.412	0.525	0.412	0.526	0.412	0.526
N	6034309	6034309	5947516	5947516	5947516	5947516

Panel B: Interactions with state-level political conditions

	(1) Value of loans	(2) Number of loans	(3) Value of loans	(4) Number of loans	(5) Value of loans	(6) Number of loans
Post × Employee contributions to Republicans	-0.0170	0.0036	0.7288***	0.0895***	0.3561***	0.0463***
	(-0.4418)	(0.6961)	(7.9120)	(7.0145)	(5.5628)	(5.0368)
Post × Employee contributions to Republicans × Republican state	0.2132***	0.0244***				
	(4.0950)	(3.5741)				
Post × Employee contributions to Republicans × State citizen liberal score			-0.0126***	-0.0015***		
			(-7.4289)	(-5.9590)		
Post × Employee contributions to Republicans × State gov. liberal score					-0.0074***	-0.0008***
					(-4.6112)	(-3.5175)
Controls	Y	Y	Y	Y	Y	Y
Lender × county FE	Y	Y	Y	Y	Y	Y
County × PPP Round FE	Y	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y	Y
Adj. R-sq	0.414	0.527	0.412	0.525	0.412	0.525
N	6048597	6048597	6021782	6021782	6021782	6021782

Table 11: Employment Effects at the County Level

This table documents the effects of partisanship on county unemployment at the lender-county level. The difference-in-differences regression is specified in Equation (4) in the lender-county-week panel data set. The dependent variable is *UI claims rate*, which is the number of initial claims per 100 people in the 2019 county labor force. The measure for partisanship is based on employee contributions (fraction of Republican-leaning employees). In column 1 (2), *(Local) Employee contributions to Republican* variable is the weighted average of fractions of (local) Republican-leaning employees, weighted by the total PPP volume originated by each lender in the given county throughout the sample period. In columns 3 and 4, *Employee contributions to Republican, moving average* variable is the weighted average of fractions of Republican-leaning employees, weighted by the total PPP volume originated by each lender during the previous 4 weeks in the given county. All variables are defined in the note of Tables 2 and A3. *t*-statistics are in the parentheses. Robust standard errors are clustered at the lender headquarter state level. Variables are winsorized at the 1st and 99th percentiles. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	UI claims rate			
Post × Employee contributions to Republicans	-0.9839*			
	(-1.9538)			
Post × Local employee contributions to Republicans		-0.7848**		
		(-2.2090)		
Employee contributions to Republicans, moving average			0.0767	0.7358**
			(1.1280)	(2.5482)
Post × Employee contributions to Republicans, moving average			-0.5824*	-0.5472*
			(-2.0487)	(-1.8935)
Post × Powerful politician	0.7401***	0.7289***	0.6581**	
	(3.1049)	(3.1360)	(2.8013)	
Post × Republican state	0.0946	0.0764	0.0855	
	(0.2550)	(0.2050)	(0.2169)	
Post × Number of PPP complaints	-0.1062	-0.0976	-0.0377	
	(-1.0540)	(-0.9682)	(-0.3595)	
Teleworkabilities	0.7510	0.9010	0.7097	
	(0.8390)	(1.0648)	(0.7623)	
Minority majority	-0.4479**	-0.3451*	-0.3514*	
	(-2.2372)	(-2.0682)	(-1.8790)	
Income per capita	0.0162	0.0159	0.0153	
	(1.1548)	(1.1846)	(1.0604)	
Population	-3.9495	-3.3181	-5.1068	
	(-0.5730)	(-0.4784)	(-0.7199)	
County FE	Y	Y	Y	N
County × PPP round FE	N	N	N	Y
Week FE	Y	Y	Y	N
Adj. R-sq	0.665	0.665	0.621	0.748
N	48074	48074	44026	43650

Table 12: PPP Lending Effects at the County Level

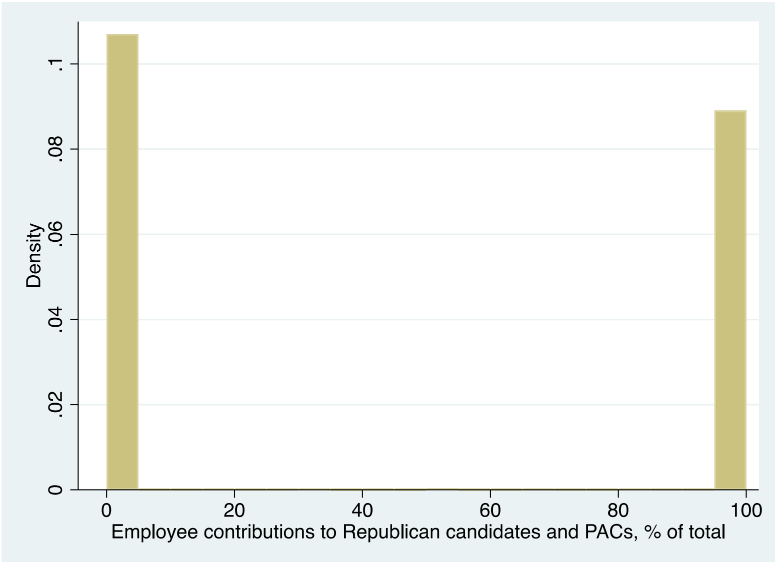
This table documents the effects of partisanship on PPP lending at the lender-county level. The difference-in-differences regression is specified in Equation (4) in the lender-county-week panel data set. The dependent variables, *Value of loans (log 1+)* and *Number of loans (log 1+),* measure the aggregated PPP loans originated within a given county in each week. The measures for partisanship are based on employee contributions (fraction of Republican-leaning employees). In columns 1 and 2 (3 and 4), the *(local) employee contributions to Republican* variable is the weighted average of fractions of (local) Republican-leaning employees, weighted by the total PPP volume originated by each lender in the given county throughout the sample period. All variables are defined in the note of Tables 2 and A3. *t*-statistics are in the parentheses. Robust standard errors are clustered at the lender headquarter state level. Variables are winsorized at the 1st and 99th percentiles. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Value of loans	(2) Number of loans	(3) Value of loans	(4) Number of loans
Post × Employee contributions to Republicans	1.1563***	0.4327***		
	(5.5174)	(3.6381)		
Post × Local employee contributions to Republicans			0.9592***	0.3072***
			(4.0619)	(3.2176)
Post × Powerful politician	-0.4716***	0.0680	-0.4848***	0.0642
	(-3.1154)	(1.2093)	(-3.1768)	(1.1056)
Republican state	0.0440	-0.2444***	0.1096	-0.2272***
	(0.2315)	(-3.1568)	(0.6229)	(-2.9736)
Post × Republican state	0.1283	0.1180	0.0981	0.1129
	(0.7712)	(1.6545)	(0.5559)	(1.5535)
Post × Number of PPP complaints	-0.7685***	-0.1637***	-0.7789***	-0.1733***
	(-9.5956)	(-5.6932)	(-10.0952)	(-5.8615)
Teleworkabilities	1.0439	-0.1452	0.9595	-0.1477
	(0.7274)	(-0.3329)	(0.6730)	(-0.3441)
Minority majority	0.4131	0.4267**	0.3648	0.4098**
	(1.1889)	(2.4292)	(0.9720)	(2.3180)
Income per capita	-0.0242	-0.0033	-0.0241	-0.0033
	(-1.4362)	(-0.8239)	(-1.4416)	(-0.8022)
Population	-7.0858**	-4.4070**	-6.9111**	-4.3406**
	(-2.6103)	(-2.5342)	(-2.5455)	(-2.3837)
County FE	Y	Y	Y	Y
Week FE	Y	Y	Y	Y
Adj. R-sq	0.626	0.872	0.626	0.872
N	117116	117116	117116	117116

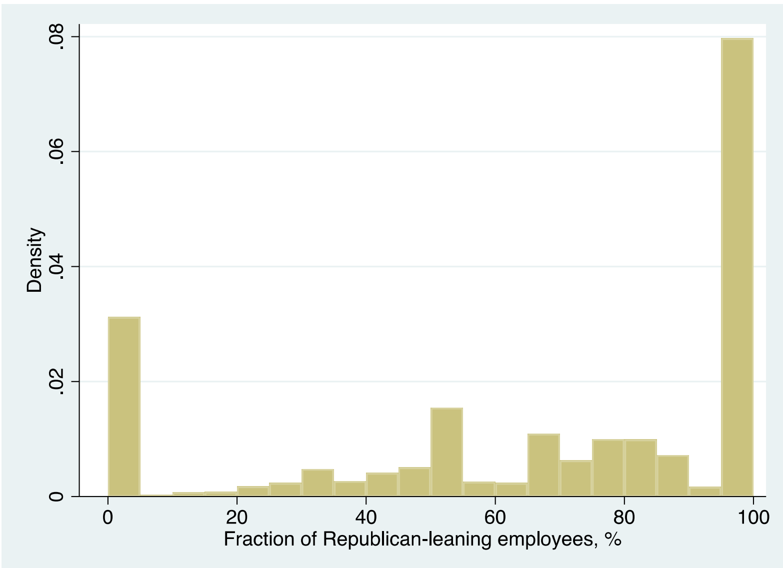
Appendix A. Supplementary Figures and Tables

Figure A1: Distribution of Lender Employee Contributions to Republicans

This figure shows the density distributions of Republican-leaning employees in PPP lenders in the 2020 election cycle. In Panel A, the distribution plots the fraction of employee contributions to Republicans over total contributions to either Democratic or Republicans at the individual employee level. The data cover 23,873 employees in 2548 PPP lenders and is based on their individual contributions to various political party and ideological PACs and candidates between 2019 and 2020. 100% indicates the employee only contributes to Republican PACs and candidates, while 0% indicating only contributing to Democrats. In Panel B, the histogram shows the employee partisanship aggregated at the lender level and describes the fraction of Republican-leaning employees for each lender. An employee is Republican leaning if her fraction of contributions to Republicans is over 50%.



Panel A: Distribution of Republican contribution fractions by lender employees (individual level)



Panel B: Distribution of fractions of Republican contributing employees (lender level)

Figure A2: Distribution of Lender Contributions to Republicans

The figure shows the density distribution of the proportion of lender PAC contributions to Republican PACs out of total contributions to both Republican and Democratic PACs in the 2020 election cycle. The data cover 59 PPP lenders and is based on their corporate PAC contributions to 253 various political party PACs between 2019 and 2020. 100% indicates the bank corporate PAC only contributes to Republican PACs, while 0% indicating only contributing to Democratic PACs.

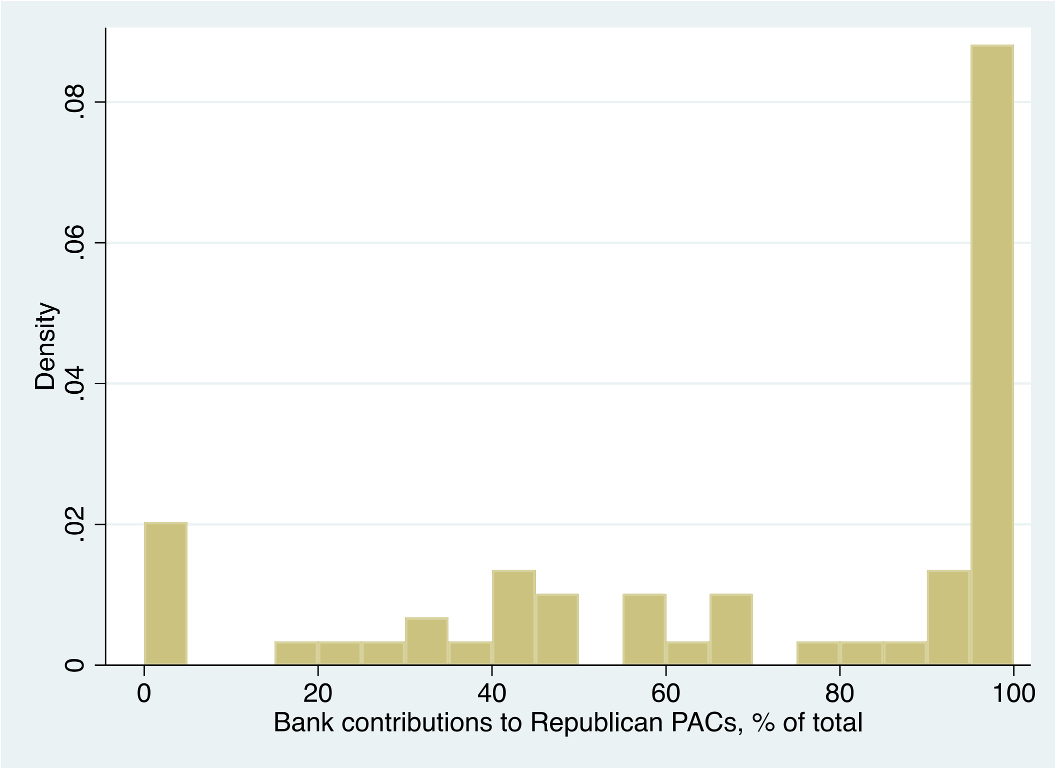


Figure A3: Parallel Trends for Lender Partisanship Based on Lender PAC Contributions

The figure shows the parallel trends for the PPP lending volume ($-amount, log) around the 2020 election cycle. Red line depicts the average total loan amount each week originated by Republican-leaning lenders, with lender partisanship (*Lender contributions to Republicans*) over sample mean. Blue line shows the weekly loan amount by Democratic-leaning & neutral lenders, with lender partisanship equal to or less than sample mean.

Table A1: 117th Congress Senate Committee Chair Ascensions

Committee	Name	State	Party	Previous Chair	Reason
Judiciary	Richard J. Durbin	Illinois	D	Lindsey Graham, of South Carolina	*Previous ranking member stepped down*
Indian Affairs	Brian Schatz	Hawaii	D	John Hoeven, of North Dakota	*Previous vice chair retired*

Table A2: Summary Statistics for Additional Variables at the Lender Level

The table presents summary statistics for additional variables of the baseline panel sample (lender-week level). The sample only keeps PPP lenders with PAC or employee contributions in the 2020 election cycle. All variables are winsorized at the 1st and 99th percentiles. *Rank-and-file employee (Executive) contributions to Republicans (number)* is the fraction of rank-and-file employees (executives) contributing more than half to Republican PACs or candidates in a given lender during the 2020 election cycle. *Number of contributing rank-and-file employees (executives)* is the number of contributing rank-and-file employees (executives) in the 2020 election cycle in a lender. *First draw loans* are the PPP loans extended to new borrowers in 2020 or in 2021 with the processing method identified as "PPP". *Second draw loans* include PPP loans extended in 2020 and those to previous borrowers in 2021 with the processing method identified as "PPS". *Loans to small (big) borrowers* are the PPP loans extended to borrowers with reported number of employees under (at least) 20.

	Obs.	Mean	S.D.	Perc. 25	Median	Perc. 75
Rank-and-file employee contributions to Republicans	79724	0.637	0.411	0.250	0.855	1
Executive contributions to Republicans	47690	0.712	0.416	0.357	1	1
Number of contributing rank-and-file employees	79724	9.736	103.169	1	1	3
Number of contributing executives	47690	2.852	11.329	1	1	2
Value of first draw loans ($thousand)	96938	2024.271	8906.834	0	50.812	298.173
Value of second draw loans ($thousand)	96938	3370.374	12948.100	0	94.151	846.734
Value of loans to small borrowers ($thousand)	96938	1362.647	4660.571	1.200	110.480	591.900
Value of loans to big borrowers ($thousand)	96938	2070.501	8170.439	0	0	341.854
Number of first draw loans	96938	28.353	92.418	0	3	14
Number of second draw loans	96938	33.892	113.548	0	3	16
Number of loans to small borrowers	96938	37.730	114.904	1	5	23
Number of loans to big borrowers	96938	4.443	16.623	0	0	1
Value of first draw loans (log 1+)	96938	8.554	5.823	0	10.836	12.605
Value of second draw loans (log 1+)	96938	9.235	6.074	0	11.453	13.649
Value of loans to small borrowers (log 1+)	96938	9.378	5.668	7.091	11.613	13.291
Value of loans to big borrowers (log 1+)	96938	4.755	6.733	0	0	12.742
Number of first draw loans (log 1+)	96938	1.701	1.620	0	1.386	2.708
Number of second draw loans (log 1+)	96938	1.779	1.666	0	1.386	2.833
Number of loans to small borrowers (log 1+)	96938	2.008	1.704	0.693	1.792	3.178
Number of loans to big borrowers (log 1+)	96938	0.594	1.072	0	0	0.693

Table A3: Summary Statistics for Additional Variables at the County-Week Level

The table presents summary statistics for additional variables of the county-week level used in Tables 11 and 12. All variables are winsorized at the 1st and 99th percentiles. *Value of loans* is the aggregated PPP loan dollar amount in thousands originated in a calendar week in a given county. *Number of loans* is the aggregated number of new PPP loans originated in a week in a given county. *Value of loans (log 1+)* is the natural logarithm of *loan amount* plus one. *Number of loans (log 1+)* is the natural logarithm of number of new loans plus one. *(Local) employee contributions to Republican* is the weighted average of fractions of (local) Republican-leaning employees, weighted by the total PPP volume originated by each lender in the given county throughout the sample period. Local employees are the contributing lender employees located in the same state of the given county. *Employee contributions to Republican, moving average* is the weighted average of fractions of Republican-leaning employees, weighted by the total PPP volume originated by each lender during the previous 4 weeks in the given county. *Powerful politician* is weighted average of the dummy variable indicating each PPP lender's headquarter in either Illinois or Hawaii, weighted by the total PPP volume originated by each lender in the given county throughout the sample period. *Republican state* is the weighted average of a dummy variable that takes the value of one if the lender headquarter is in a state controlled by Republican in 2020, zero otherwise. *Number of PPP complaints in CFPB* is the weighted average number of consumer complaints mentioning PPP since 2020 from CFPB for each PPP lender. *Number of CFPB* complaints (log 1+) is the natural logarithm of number of PPP complaints plus one.

	Obs.	Mean	S.D.	Perc. 25	Median	Perc. 75
Value of loans ($thousand)	121942	4063.820	14301.754	54.415	306.787	1500.634
Number of loans	121942	70.279	193.618	3	14	46
Value of loans (log 1+)	121942	11.886	4.131	10.904	12.634	14.221
Number of loans (log 1+)	121942	2.748	1.681	1.386	2.708	3.850
Employee contributions to Republicans	121924	0.633	0.197	0.505	0.653	0.784
Local employee contributions to Republicans	121810	0.670	0.228	0.513	0.706	0.857
Employee contributions to Republican, moving average	111192	0.610	0.234	0.448	0.621	0.793
Powerful politician	121942	0.033	0.179			
Republican state	121942	0.517	0.500			
Number of PPP complaints in CFPB	121924	2.375	3.237	0.190	0.890	3.303
Number of CFPB complaints (log 1+)	121924	0.873	0.783	0.174	0.637	1.459

Table A4: Cross-Sectional Comparison Between Republican-Leaning and Democratic-Leaning/Neutral Banks

The bank characteristics based on the call reports in the last quarter before the 2020 election. *Republican leaning* banks are the ones with partisanship based on employee contributions to Republican larger than sample mean. All the rest banks are *Democratic leaning and neutral*. In Panel A, we use t-tests with unequal means to compare the characteristics, as well as *Estimated probability of Republican leaning*, using a probit regression on *Bank Size, ROA, NPL, Tier1 ratio,* and *core deposits* as independent variables. In Panel B, we run the same t-test in a matched sample based on *Estimated probability of Republican leaning* following a propensity matching method.

Panel A: Full sample

	Republican leaning		Democratic leaning and neutral		T-test	
	Obs.	Mean	Obs.	Mean	Difference	*t*-stat.
Employee contributions to Republicans	1303	0.98	842	0.28	0.70***	(77.28)
Bank size	1303	13.00	842	13.87	-0.87***	(-13.01)
Bank ROA	1303	1.55	842	1.21	0.34***	(5.34)
Bank NPL	1303	0.89	842	0.78	0.11**	(2.57)
Bank Tier1 ratio	1303	10.72	842	10.37	0.35***	(3.02)
Bank core deposits	1303	61.91	842	57.73	4.18***	(4.96)
Est. prob. of Republican leaning	1303	0.64	842	0.55	0.10***	(14.12)

Panel B: Matched sample

	Matched Republican leaning		Democratic leaning & neutral		T-test	
	Obs.	Mean	Obs.	Mean	Difference	*t*-stat.
Employee contributions to Republicans	1601	0.95	806	0.28	0.68***	(71.88)
Bank size	1601	13.65	806	13.68	-0.02	(-0.37)
Bank ROA	1601	1.27	806	1.23	0.03	(0.51)
Bank NPL	1601	0.78	806	0.79	-0.01	(-0.36)
Bank Tier1 ratio	1601	10.43	806	10.44	-0.01	(-0.12)
Bank core deposits	1601	58.01	806	58.38	-0.37	(-0.44)
Est. prob. of Republican leaning	1601	0.57	806	0.57	0.00	(0.50)

Table A5: Summary Statistics for Additional Variables at the Lender-County-Week Level

The table presents summary statistics for the key variables of the lender-county-week level used in Tables 9 and 10. The sample only keeps PPP lenders with employee contributions in the 2020 election cycle. All variables are winsorized at the 1st and 99th percentiles. Panel A tabulates summary statistics of a number of variables. *Value of loans* is the aggregated loan dollar amount originated in a calendar week by a given lender in a given county. *Number of loans* is the number of new PPP loans originated in a week by a given lender in a given county. *Value of loans (log 1+)* is the natural logarithm of *loan amount* plus one. *Number of loans (log 1+)* is the natural logarithm of number of new loans plus one. *Employee contributions to Republicans* is the fraction of employees contributing more than half to Republican PACs or candidates in a given lender during the 2020 election cycle. The *local employee contributions to Republicans* is the fraction of employees locating in the same state of a given county contributing more than half to Republican PACs or candidates in a given lender during the 2020 election cycle. *Powerful politician* is the dummy indicator on whether the lender headquarter state is either Illinois or Hawaii. *Republican state* is a dummy variable that takes the value of one if the given county is in a state controlled by Republican in 2020, zero otherwise. *Number of PPP complaints in CFPB* is the number of consumer complaints mentioning PPP since 2020 from CFPB. *Number of CFPB* complaints (log 1+) is the natural logarithm of number of PPP complaints plus one. *Bank size* is the natural logarithm of one plus bank's total assets in the previous quarter. *Bank ROA (%)* is quarterly net income*4/total assets*100, lagged one quarter. *Bank NPL (%)* is loans past due 90 days or more and nonaccruals over total loans *100, lagged one quarter. *Bank Tier1 (%)* is tier one capital over total loans *100, lagged one quarter. *Bank core deposits (%)* is the sum of transactions deposits and all other savings deposits that are included in total non-transaction accounts, excluding MMDAs, over total deposits *100, lagged one quarter. *Minority majority county* is a dummy variable that takes the value of one if the non-white population is over 50% of total population in 2019, zero otherwise. *Income per capita* is county personal income per capita in $thousands in 2019. *Local workforce teleworkability* is the weighted average of Occupational Information Network derived work-from-home score from Dingel and Neiman (2020), weighted by the number of employments under each NAICS code for a given county in 2019. *State citizen liberal score* is the revised 2016 citizen ideology series following Berry et al. (1998). *State government liberal score* is the 2017 state government ideology measure following Berry et al. (1998). Panel B reports the correlation tables among the county-level characteristics.

Panel A: Summary statistics

	Obs.	Mean	S.D.	Perc. 25	Median	Perc. 75
PPP lending						
Value of loans ($thousand)	7374698	34.425	179.299	0	0	0
Number of loans	7374698	0.586	2.462	0	0	0
Value of loans (log 1+)	7374698	1.555	3.893	0	0	0
Number of loans (log 1+)	7374698	0.182	0.531	0	0	0
Lender Partisanship						
Employee contributions to Republicans	7374698	0.575	0.368	0.267	0.600	1
Local employee contributions to Republicans	3119610	0.631	0.379	0.333	0.707	1
Other determinants of PPP lending						
Powerful politician	7374698	0.042	0.201			
Republican state	7373900	0.492	0.500			
Number of PPP complaints in CFPB	7374698	2.476	10.470	0	0	0
Number of PPP complaints (log 1+)	7374698	0.283	0.885	0	0	0
Bank size (log 1+)	6051172	15.130	2.337	13.458	14.585	16.497
Bank ROA (%)	6051172	2.280	2.303	0.863	1.587	3.286
Bank NPL (%)	6049504	0.786	0.799	0.320	0.549	0.955
Bank Tier1 ratio (%)	6051172	9.460	2.364	8.156	9.080	10.269
Bank core deposits (%)	6050164	54.957	20.164	40.375	57.963	70.003
Minority majority county	7357560	0.059	0.235			
Income per capita	7248120	0.051	0.016	0.041	0.047	0.056
Local workforce teleworkability	7248120	0.303	0.056	0.263	0.296	0.339
State citizen liberal score	7343728	50.627	11.441	44.412	50.380	57.189
State government liberal score	7343728	36.446	16.595	23.613	26.555	49.629

Panel B: Correlations

	Minority majority	Income per capita	Telework.	Republican state	State citizen liberal score	State gov. liberal score
Minority majority county	1					
Income per capita ($thousand)	-0.0771***	1				
Local workforce teleworkability	0.0255***	0.660***	1			
Republican state	0.0417***	-0.218***	-0.168***	1		
State citizen liberal score	0.0178***	0.303***	0.311***	-0.586***	1	
State government liberal score	0.00331***	0.324***	0.255***	-0.730***	0.721***	1

Appendix B. Manual Matching Individual Contributors' Employers to PPP lenders

We match the employers of individual contributors in the 2020 election cycle to the PPP lender sample. The public individual contribution data contains the donor's names, self-reported occupations and employers, as well as location information including city, state and zip. The number of individual contributors is multifold of that in the previous election cycles due to the inclusion of small donors under $200 for online contribution platforms. We match over 4.8 million donors to our lender sample as follows.

First, we use different fuzzy match program to link the self-reported employer names to the PPP lender names from SBA, the bank legal names and short names from Call Reports, and holding company names from FRY-9C, if any. Specifically, we employ STATA commands *reclink2* with default setting based on "bigram" keeping all matched pairs with the matching score over 0.6; and *matchit* based on "token" keeping all pairs with score over 0.9. This step results in over 220k potential matched name pairs.

Second, we manually go through the potential matched pairs and confirmed around 78k pairs, involving 39568 individual donors and 3398 banks. The resulted potential pairs often involve an individual donor matched to multiple employer banks. This one-to-many ambiguous matches could be due to an employee changing jobs during the 2020 election cycle. However, it could also be due to errors, since the reported employer names may be unstandardized trade names or historical names, and many banks have very similar names.

Third, we gauge the ambiguous matches based on the location information. If a donor match to more than one bank, and only one matched bank's headquarter is in the same city/state of the donor, we keep the same location bank as the correct match. For the remaining one-to-many matches, we check if only one matched bank's branch is in the same city/state of the donor and keep it as the correct match.

Fourth, for the remaining ambiguous donors (also including individual donors where the employer information is simply "bank" or "finance") involving over 3000 donors, we record the accurate employer information during the PPP sample period by googling their names and location and using the public information from LinkedIn or bank information pages or news releases. In this step, we also confirm the correct matches due to individual donors changing jobs among different banks and remove individual donors that did not work at any banks between 2020 and 2021. If we cannot track down a particular employee in LinkedIn or any viable sources, we pick the bank with a similar name to the reported employer that has a branch closest to the donor. If we are not able to find any matched lender for a donor after all previously mentioned steps, we drop the donor from the sample. We also remove contributions to non-partisan PACs and independent candidates.

The final mapping between PPP lenders and bank contributing employees are around 40k matched pairs and over 350,000 contribution records, including 23,873 employees working for 2548 lenders. We also identify the bank executives based on the reported occupations, supplemented with the information collected from LinkedIn and viable webpages during the manual matching. Specifically, a bank employee is "*executive*" if her title or reported occupation is (bank/banking) executive, chairman, president, (board of) director(s), managing director, CEO (or chief exec(utive) off), CFO, COO, CTO, CIO, or senior/executive vice president. Otherwise, we consider the employee as “*rank-and-file*”.