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Small business lending under the PPP and PPPLF programs[☆]

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ABSTRACT

We use Call Report data to examine the effects of the Paycheck Protection Program (PPP) and the PPP Liquidity Facility (PPPLF) on small business and farm lending by individual commercial banks. As program participation was associated with small business lending, we adopt an instrumental variables approach to identify causal implications based on historical bank relationships with the Small Business Administration and the Federal Reserve's discount window. Our results indicate that both programs encouraged lending growth over the first half of 2020. However, while the PPP encouraged greater lending across all banks, only small and medium-sized bank lending growth was significantly related to participation in the PPPLF.

1. Introduction

The start of the COVID-19 pandemic in the U.S. in the early months of 2020 and the accompanying quarantines and work-from-home orders severely affected the viability of many small businesses, especially those in the retail and service sectors. Small businesses play an integral role in the U.S. economy and particularly in the labor market, accounting for nearly 47% of total employment and 41% of private-sector payrolls in the U.S.[1] To address this unprecedented challenge directly, the U.S. Congress created and funded the Paycheck Protection Program (PPP) to help firms retain their employees and cover other ongoing expenses. The PPP was administered through the Small Business Administration (SBA), which in turn relied on commercial banks and other financial institutions to originate forgivable loans to qualified firms. In addition, the Federal Reserve established the PPP Liquidity Facility (PPPLF) to provide loans to PPP lenders using the underlying PPP loans as collateral.

This paper focuses on the role that these two programs had in maintaining the flow of bank loans to small and medium-sized enterprises (SMEs) during the first half of 2020. In particular, we examine the effect that a bank's participation in the PPP and the PPPLF had on its SME lending, as per regulatory Call Report filings up through the second quarter of 2020.

Several studies have established a positive correlation between both PPP and PPPLF participation and growth in SME lending (e.g., see Beauregard et al. (2020)). However, the establishment of a causal link between participation in these two programs and SME lending raises the challenge of the endogeneity of banks' program participation decisions. Lenders faced a joint set of decisions under these COVID-related support programs; that is, whether or not to extend a loan to a particular firm during this period, whether that loan would be submitted through the PPP, and whether to borrow under the Fed's PPPLF program using the loan as collateral. The latter two decisions clearly affected the expected returns and risks that a bank would face on a given loan and hence had implications on whether a bank would be willing to extend that loan. All of these considerations likely affected SME lending growth by banks in the first half of 2020.

To address the endogeneity of PPP and PPPLF participation relative to SME loan growth, we use instrumental variables estimation. Our first

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[1] See The U.S. Small Business Administration (2019). The definition of small business used here is an independent business with less than five hundred employees.

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instrument incorporates measures of the intensity of banks' interaction with the SBA in 2019, just prior to the crisis. Greater exposure to SBA lending prior to the crisis likely facilitated a bank's willingness to participate in the PPP. For example, banks already certified as SBA 7(a) lenders prior to the launch of the PPP were automatically eligible for the program. Several studies have shown that PPP lending was greater in areas that were more served by the SBA in 2019 (see Liu and Volker (2020)) and much less correlated with the economic conditions prevailing shortly after the COVID outbreak (see Granja et al. (2022)).

Our next set of instruments relates directly to a bank's relative ease in participation in the PPPLF. Since the PPPLF was administered by the Federal Reserve, familiarity with that institution going into the crisis likely facilitated participation in the program. We consider indicators of familiarity with the Federal Reserve discount window, as per Anbil et al. (2021). Specifically, we use two measures based on proprietary Federal Reserve data: a count of documents on file for a bank at the discount window and the total collateral pledged to the discount window program, with both values calculated for each bank at year-end 2019. Anbil et al. (2021) show these variables to be correlated with the share of PPP loans that were converted into cash under the PPPLF. As discussed above, we consider the decision to issue a PPP loan as sensitive to the perceived ease with which it could be converted into cash by submitting it as collateral to the PPPLF. As such, we expect that these instrumental variables will likely influence both PPP and PPPLF participation. We use all three variables as instruments for participation in both the PPP and PPPLF programs.

Our base instrumental-variables regression shows that increased bank participation in these programs is a key explanatory variable for growth in SME lending in the first half of 2020. On average, our coefficient estimates suggest that a one standard deviation increase in our PPP participation measure is associated with a 32 percentage point increase in SME lending growth relative to year-end 2019, and a one standard deviation increase in PPPLF participation has a roughly 33 percentage point impact. We subject these results to a battery of sensitivity tests, including a variety of changes in the regression specification and estimation techniques.

Our bank-level specification allows us to condition on a variety of firm-specific characteristics, discussed in detail below. Among those conditioning variables that had significant effects in our regressions, we find that SME lending growth was much higher among small and medium-sized banks. This result matches Li and Strahan (2021), who argue that relationship lending was an important driver of the PPP's successful implementation.[2] We also find that banks with stronger capital positions and more stable funding, such as having more core deposits, engaged in more SME lending in the first half of 2020, suggesting that banks in sounder condition were able to increase their lending during this challenging period and with the support of these government lending programs.

We also identify disparities by bank size and loan type in the effect of the programs. Separating our sample into subsamples of large and of small to medium-sized banks, we find that PPP participation encouraged greater SME lending across all banks. However, only SME lending growth by small to medium-sized banks was significantly related to participation in the PPPLF. Our results therefore support the conclusion made by some (e.g., Bowman (2020)), that the PPPLF was of particular importance to smaller institutions, who faced notable liquidity implications of rapidly expanding SME lending through participation in the PPP. Furthermore, subjecting growth in small business and farm lending independently to our base specification, we find that participation in both programs were significant predictors of growth in small business lending, but not small farm lending.

To differentiate between lending through the PPP and outside of that program, we decompose our dependent variable – a bank's aggregate SME loan growth – into growth rates for PPP lending and non-PPP lending. When these growth rates are examined separately, we find that non-PPP lending decreases for small to medium-sized banks but not for large banks, suggesting that small to medium-sized banks did substitute their SME lending towards both programs in response to the credit guarantees and liquidity advantages they provided.

Our paper contributes to the literature that most directly focusses on bank responses – such as bank lending growth – to these government programs. Marsh and Sharma (2022) develop a Bayesian model of a bank's PPP participation decision to address the likely endogeneity of that decision. They find that PPP participation was an important driver of loan growth, which our empirical results support. Li and Strahan (2021) merge bank balance sheet data with loan-level PPP data to examine banks' SME lending in the first half of 2020. They find that lending grew more at banks with business models more typically associated with close borrower relationships, which is often referred to as relationship lending; that is, smaller banks, banks with high levels of SME lending, banks with high levels of credit commitments, and banks more reliant on retail deposits. Furthermore, they find that the majority of lending growth took place within the PPP program. Karakaplan (2022) also examines bank-level loan growth as a function of PPP participation using the SBA loan-level data. Focusing on PPP loans of less than $1 million that match the small business loan definition used for bank regulatory filings, he found statistically significant net complementarities between PPP lending and conventional SME lending. This result holds for both business loans and commercial real estate loans. These results contrast with our findings below, as well as Chodorow-Reich et al. (2022) which finds that the mainly large banks in their sample experienced less conventional lending, suggesting that PPP borrowing served as a substitute for conventional borrowing under the pandemic.

The remainder of the paper is structured as follows. Section 2 provides details on both the PPP and the PPPLF. Section 3 presents our data and empirical design. Section 4 presents our main results, while Section 5 summarizes a number of additional robustness results. Section 6 presents our empirical results regarding non-PPP lending, and Section 7 concludes. Our appendixes include several additional robust tests and empirical results.

2. Program details

In response to the health and economic emergencies caused by the COVID-19 virus, the Coronavirus Aid, Relief, and Economic Security (CARES) Act, a $2.2 trillion spending program, was signed into law on March 27, 2020. We focus here on a key component of the legislation – the Paycheck Protection Program (PPP) – that was intended to provide immediate relief to small businesses and help avoid business failures; see Hubbard and Strain (2020) and the survey by Berger and Demirgüç-Kunt (2021) for further details. The nearly $700 billion program was administered by the Treasury Department through the Small Business Administration (SBA). The PPP contained several components, but our analysis concentrates on the nearly $350 billion program for forgivable loans that would be used to pay up to eight weeks of payroll costs as well as certain immediate operating costs, such as rent and utilities. Businesses were permitted to borrow up to 2.5 times their average monthly payroll costs, capped at $10 million. The loans carried minimal risk to borrowers since they could be forgiven if certain conditions were met, such as maintaining employee headcount or salary levels during the 24-week period (originally an eight-week period) after the loan was originated.

[2] Earlier studies suggest such relationships have been important after financial shocks, as shown empirically after the Lehman Brothers default by Banerjee et al. (2021) and theoretically in the work of Boot and Thakor (1994) as well as Boot and Thakor (2000). Berger et al. (2021b) provide evidence for an alternative view regarding lending terms during the pandemic period, however.

The loans were mainly underwritten by banks and carried a government guarantee.[3] The PPP allowed banks to charge an interest rate of up to 5% of principal on loans up to $350,000, 3% on loans between $350,000 and $2 million, and 1% on loans between $2 and $10 million. Although interest rates on these loans were low, banks received SBA fee payments that were a decreasing function of loan size. Importantly, PPP loans were assigned a zero weight for risk-weighted bank capital requirements. Finally, lenders were not held responsible for borrower misrepresentations, although anti-money-laundering compliance programs were still required. Thus, the PPP provided banks and potential borrowers with a relatively attractive package of loans and fees that were of mutual benefit.

The program was extended by the Paycheck Protection Program and Health Care Enhancement Act, which was enacted on April 24, 2020. The revised legislation increased PPP funding by $320 billion to roughly $670 billion. Further refinement of the program via the Paycheck Protection Program Flexibility Act (PPPFA) was signed into law on June 5, 2020. This Act extended the covered period for the forgivable loans from eight weeks to 24 weeks (or until December 31, 2020). The PPPFA also allowed businesses to spend 40 percent of forgivable funds on non-payroll expenses.

Further PPP extension was provided by the Economic Aid to Hard-Hit Small Businesses, Nonprofits and Venues Act (the "Economic Aid Act"), which passed into law in late December 2020 and authorized a third round of PPP loans with an additional $284 billion in funding. The legislation focused on providing new PPP loans to small businesses that had not received one and allowed certain existing borrowers to apply for a second loan. The legislation also targeted previously under-represented borrowers by limiting new loans to those underwritten by SBA-designated Community Financial Institutions and other small lenders. In addition, certain loan funds were designated for very small businesses (10 or fewer employees) and for loans below $250,000 made in low- or moderate-income neighborhoods.

With regards to agricultural production lending, the first set of PPP terms were based on existing SBA rules, which created eligibility and loan limits based on positive 2019 net farm profits; see FORV/S (2020). Due to widespread farm losses in 2019, this restriction limited PPP access to many self-employed farmers. In addition to providing additional funding for loan programs within the Department of Agriculture, the Economic Aid Act changed PPP application requirements for agricultural borrowers to the less restrictive condition of positive 2019 reported gross income.

The Federal Reserve was a major participant in the pandemic recovery effort, mainly through loan facilities funded by the Treasury Department that purchased selected credit products from banks and thus provided them with additional liquidity and lending capacity. On April 8, the Federal Reserve established the PPPLF, which was designed to provide credit to eligible financial institutions that originated PPP loans by taking these loans as collateral at face value (e.g. Liu and Volker (2020) and Anbil et al. (2021)). Initially, the facility was limited to only depository institutions, but the eligibility requirements were extended to all SBA-qualified PPP lenders as of May 2020.

The terms of the PPPLF are relatively straightforward. No fees are charged, and credit is provided at an interest rate of 35 basis points. PPP loans are used as collateral and are priced at face value. Purchased PPP loans can be posted as collateral, but partial shares are not eligible. The PPPLF loan amount and maturity are set equal to the terms of the pledged PPP loan, and the maturity date is accelerated in cases of loan forgiveness, default, or retirement via SBA purchase. In addition to providing funding support to the PPP, the federal banking regulatory agencies further allowed banks to exclude any PPP loans used as PPPLF collateral from leverage-based regulatory capital and liquidity requirements (e.g. Liu and Volker (2020)). This feature provided another useful incentive to use the facility since its use removed the need for banks to hold regulatory capital against these pledged loans. Participation in the PPPLF as of the second quarter of 2020 was reasonably high at about 1300 banks (about 27% of our sample) and about 15% of outstanding PPP loans being pledged as collateral.

[3] Non-bank lenders, particularly so-called 'fintech' lenders, also participated in the PPP program, as summarized by Griffin et al. (2022); see also Erel and Liebersohn (2022) as well as Chernenko and Scharfstein (2022).

Table 1
PPP and PPPLF counts.

Panel A. Number of banks				
Program	Small	Medium	Large	Total
Both	1072	155	42	1269
PPP only	2879	461	85	3425
Neither	31	1	0	32
Total	3982	617	127	4726
Panel B. Share of PPP lending (%)				
Program	Small	Medium	Large	Total
Both	6.5	8.0	10.2	24.7
PPP only	10.4	16.7	48.2	75.3
Neither	0.0	0.0	0.0	0.0
Total	16.9	24.7	58.4	100.0

Note: Call Report data as of 2020.Q2. Participation in PPP program is defined as having a value greater than 1% for the PPPR variable, which is the ratio of a bank's PPP participation to its total small business and farm lending. The total dollar amount of PPP lending as of 2022.Q2 is $480 billion. The bank size categories are defined based on asset size as of 2019.Q4; i.e., small banks have total assets below $10 billion, large banks have total assets exceeding $100 billion, and medium banks have total assets between those two thresholds.

Table 1 provides a summary of the number of banks in our sample participating in the PPP and PPPLF as of the second quarter of 2020 based on the three size categories that we define in the following section. Panel A shows that of the 4726 banks in our base sample, only 32 of them did not participate in the PPP, almost all of which were smaller community banks. 72% of the banks participated in the PPP only, with about 84% of those banks being in the small bank category, reflecting broad participation in the PPP. Furthermore, 27% of banks participated in both the PPP and PPPLF with again small banks making up nearly 85% of that sub-sample. Panel B shows the percentage share of total PPP lending in our sample, where the ratios are the aggregate PPP loan amounts in each cell divided by $480 billion, the total PPP loan amount for our sample of commercial banks. The largest dollar amount of PPP (almost 50% of the total) was originated by large banks that did not access the PPPLF, whereas the most populated category of small banks that did not access the PPPLF accounted for just 10% of the total. The total amount of PPP loans pledged to the PPPLF by the banks in our sample is roughly $63 billion, which accounts for 93% of total PPPLF lending in the second quarter of 2022. Interestingly, while large bank lending represented more than half of the dollar value of PPP loans extended, participation in the PPPLF was much more evenly distributed, reflecting the disproportionate importance of the PPPLF program for small and medium-sized banks.

3. Data and methodology

3.1. Data and variable definitions

Our main dataset is the quarterly bank-level regulatory filings obtained from the Federal Financial Institutions Examination Council's "Call Reports", which provide detailed information on both balance sheet and income statement variables. All data is measured as of quarter-end. We use 2019.Q4 data to characterize bank conditions going into the pandemic and 2020.Q2 data to examine SME lending under the PPP and PPPLF programs.

Our sample is a cross-section of U.S. commercial banks. Because we are interested in SME lending growth, banks must have reported some level of small business or farm lending on their Call Reports in 2019.Q4 to be included in the sample. We separate reporting banks into three categories based on asset size in 2019.Q4; i.e., small banks with assets below \$10 billion, large banks with assets exceeding \$100 billion, and a middle category between them. As noted in Table 1, our base specification contains 4726 banks, of which 3982 are classified as small banks, 617 as medium-size banks, and 127 as large banks. We adopt the Call Report definition of small business and farm lending as business loans of \$1 million or less and farm loans of \$500,000 or less, respectively.

We characterize PPP and PPPLF participation through the variables PPP and $PPPLF$, respectively. PPP is defined as the ratio of PPP participation, as per Call Report filings, to total small business and farm lending.[4] The PPP permitted loans exceed both our small business and farm lending level thresholds, going as high as \$10 million. As a result, it is possible, and happens in practice, that bank values of PPP can exceed one. In response, we winsorize the data at a 2.5%–97.5% level, which reduced the highest value of PPP to approximately 0.85. $PPPLF$ is defined as the ratio of bank borrowing from the PPPLF program relative to total lending through the PPP.[5] Again, the differing loan size definitions in the data allow for the maximum value of $PPPLF$ to exceed one, and we respond by also winsorizing at the 2.5%–97.5% level.

Our dependent variables are primarily measures of growth in lending to small businesses and farms between 2019.Q4 and 2020.Q2 at the bank level. The dependent variable in our base specification is $\Delta BUSF$, which measures growth in small business and farm lending over that interval. Similarly ΔBUS and $\Delta FARM$ represent growth in small business and farm lending only, respectively, over that same interval.

We examine growth in bank lending over this period while conditioning on differences in individual bank characteristics established prior to the COVID period. Other research has shown the importance of conditioning for disparities in bank characteristics in these types of studies; for example, Cornett et al. (2011) demonstrated that financially constrained banks were more limited in their credit extension during the global financial crisis. We follow the literature, such as Rice and Rose (2016) as well as Li and Strahan (2021), in the determination of Call Report conditioning variables to include in our specification. We then calculate and use pre-pandemic 2019.Q4 values.

We include $LIQUIDITY$, which measures bank cash and security holdings as a share of total assets, as a measure of bank liquidity. We also include $DEPOSITS$, which measures core deposits relative to total assets as a measure of a banks' reliance on deposit funding. We also include $CAPRAT$, a measure of the total capital ratio, to capture bank capital positions, and $COMMITMENT$ as a measure of outstanding loan commitments, which have been shown to play a major role in encouraging lending during the COVID crisis (e.g., Greenwald et al. (2020)). As a number of banks experienced exceptionally large changes in their funding composition over this period, we also include a variable $\Delta DEPOSITS$ to condition for changes in the share of core deposit funding between 2019.Q4 and 2020.Q2.

Industry sectors with firms that are familiar with the SBA prior to the pandemic may have received disproportionate assistance from government pandemic programs, including the PPP and PPPLF, and therefore may have received more credit than other industry sectors, all else equal. Banks with relative expertise in lending to such industries may therefore have had an advantage in meeting this extra demand and therefore experienced greater lending growth during the pandemic than other banks. In response, we therefore consider the similarity in a bank's small business and farm lending mix by industry (based on six-digit NAICS codes) with that of the SBA overall at year-end 2019. Our $INDMIX_i$ is specified as the sum over all industries j of the product of the share of SBA lending in industry j and the share of bank small business and farm lending in industry i. $INDMIX_i$ satisfies

$$INDMIX_i = \sum_j \left(\frac{SBA_j}{SBA} \cdot \frac{LOANS_{i,j}}{LOANS_i} \right), \tag{1}$$

where SBA_j represents SBA lending to industry j, SBA represents total SBA lending, $LOANS_{i,j}$ represents small business and farm lending by bank i in industry j, and $BUSF_i$ represents total bank i small business and farm lending. All values are measured for the duration of 2019. It is easy to verify that $INDMIX_i$ is increasing in the similarity of the industry mixes of bank i and the SBA.

3.2. Estimation

Our base specification uses two-stage least squares estimation, with the included instrumental variables discussed below. We include each of the endogenous variables one at a time.[6] Our dependent variables, denoted generically as $\Delta LOANS_i$, are the different measures of growth in a bank's SME lending in the first half of 2020. For the estimation considering the effect of PPP participation on small business and farm lending growth, the second stage satisfies

$$\Delta LOANS_i = c + \beta_1 PPP_i + \beta X_i + \beta_2 SMALL + \beta_3 MED + \epsilon_i \tag{2}$$

where X_i denotes the set of conditioning variables discussed above, $SMALL$ and MED are indicator variables representing small and medium-sized banks, and ϵ_i is the regression residual. Similarly, for the estimation considering the effect of PPPLF participation on small business and farm lending growth, the second stage satisfies

$$\Delta LOANS_i = c + \beta_1 PPPLF_i + \beta X_i + \beta_2 SMALL + \beta_3 MED + \epsilon_i \tag{3}$$

where X_i again denotes the set of conditioning variables discussed above.

We cluster our standard errors by bank size. We allow for three clusters, representing small, medium, and large banks, respectively. There are a variety of reasons to expect that standard errors may be correlated across groups sorted by bank size. Large banks have quite different funding and lending opportunities than those enjoyed by small and even medium-sized banks. On the funding side, the greater ability of large banks to issue their own commercial paper might make them much less sensitive to the use of the PPPLF program (and by association the PPP program as well) than smaller banks that tend to have greater relative reliance on traditional deposit funding. On the lending side, large banks rely relatively less on small business and farm lending.

As a robustness check, we also cluster our standard errors on the basis of geography, by US geographic regions. Several studies

[4] Call Report data is compulsory for regulated banks, so this data source has no issues concerning potential endogeneity in reporting patterns. The Call Report was restructured as of 2020.Q2 to collect information on PPP loan origination and PPPLF participation. The relevant SME lending data are reported on Schedule RC-C, Part II of the Call Report. PPP loans are aggregated into total SME lending on that Schedule RC-C, Part II, and they are reported separately as a memorandum item on Schedule RC-M. Accordingly, when PPP loans are sold, repaid, or forgiven, they lead to a reduction in dollar amounts on both schedules.

[5] In the Call Report, PPP loans pledged as collateral to the PPPLF are only reported as a memorandum item on Schedule RC-M. When these loans are no longer needed as collateral, the dollar amount of the memorandum item is reduced.

[6] We also generated results for the specification that includes both endogenous variables, reported in the online appendix https://www.frbsf.org/wp-content/uploads/sites/4/wp2021-10_appendix.pdf, as discussed in the robustness check section below. With both endogenous variables included, PPP continues to enter significantly with a positive coefficient, while $PPPLF$ is insignificant. However, this specification does not pass the weak instrument test. We obtain a Cragg-Donald statistic of 6.36, which is below the 6.46 Stock Yogo 20% confidence interval threshold.

Table 2
Summary statistics.

Panel A. Full sample of banks				
	Mean	Sd	Min	Max
Δ BUSF	0.280	0.373	−0.180	1.659
Δ BUS	0.338	0.372	−0.186	1.602
Δ FARM	−0.002	0.195	−0.453	0.715
PPP	0.285	0.263	0.000	1.076
PPPLF	0.087	0.252	0.000	0.995
Observations	4726			
Panel B. Sample of banks accessing the PPPLF				
	Mean	Sd	Min	Max
Δ BUSF	0.298	0.472	−0.180	1.659
Δ BUS	0.331	0.475	−0.186	1.602
Δ FARM	−0.006	0.216	−0.453	0.715
PPP	0.263	0.332	0.000	1.076
PPPLF	0.578	0.368	0.000	0.995
Observations	1269			

Note: These summary statistics are subsequent to winsorizing for the first half of 2020. $\Delta BUSF$ represents growth in aggregate small business and farm lending; ΔBUS and $\Delta FARM$ represent growth in small business and small farm lending, respectively; PPP is the ratio of PPP participation to aggregate small business and farm lending; and $PPPLF$ is the ratio of borrowing from the PPPLF program to PPP lending.

have identified a geographic footprint to PPP participation. All of the variables perform similarly to the specifications reported here with clustering by bank size. These results are also available in our online appendix at https://www.frbsf.org/wp-content/uploads/sites/4/wp2021-10_appendix.pdf.

We also consider estimation under the control function method as a robustness check, which uses the residuals from instruments as additional regressors in order to address the potential endogeneity problem. Formally, this entails the addition of the residual of the endogenous variable regressed on the instruments and the control variables to our specification. For example, for the estimation considering the effect of PPP participation on small business and farm lending growth, the specification under the control function method satisfies

$$\Delta LOANS_i = c + \beta_1 PPP_i + \beta X_i + \beta_2 SMALL + \beta_3 MED + \widetilde{PPP_i} + v_i \quad (4)$$

where $\widetilde{PPP_i}$ is the aforementioned residual and v_i is an i.i.d. error term under ordinary least squares. As discussed in Wooldridge (2010), this method is asymptotically equivalent to two stage least squares with one endogenous regressor.

3.3. Summary statistics

Summary statistics for our main variables of interest for the first half of 2020 and subsequent to winsorizing are shown in Table 2. Panel A shows the values for the largest regression sample in our analysis, and Panel B shows the summary statistics for the sample of banks that accessed the PPPLF. The full dataset exhibits a healthy degree of variability in small business and farm lending growth (BUSF), the dependent variable of our base specification. On average, bank lending of this type grew rapidly at the start of the pandemic, with total values ranging from approximately −18% to 166%. Growth in small business lending alone ranged from −11% to 160% with a mean value of 34%, while growth in small farm lending alone was close to zero on average and ranged from −45% to 71%.

Panel B shows the summary statistics for the 1269 banks in the sample that accessed the PPPLF. Note that their PPPLF ratio values averaged 58%, relative to just 9% for the full sample. Otherwise, the summary statistics for this sample are very similar to those of the full sample, suggesting again that the PPPLF was accessed by a wide variety of eligible banks.

3.4. Identification

Participation in the PPP and PPPLF programs is likely endogenous to changes in bank lending activity during this early stage of the COVID crisis. Lenders faced a joint set of decisions under the program; namely, whether or not to extend a loan, whether or not that loan would be submitted to the PPP, and whether or not to use the loan as collateral under the PPPLF. The latter two decisions clearly affected the expected returns and risks that banks would face on a given loan, and hence also had implications on the terms under which a bank would be willing to extend that loan. All of these considerations are likely to affect the volume of growth in SME lending experienced by banks over this period.

To respond to the likely endogeneity of PPP and PPPLF participation, we use instrumental variables estimation. We consider two types of instruments. First, we consider the intensity of bank interaction with the Small Business Administration (SBA) that was responsible for administering PPP lending in 2019, prior to the crisis. It is quite likely that greater connections to the SBA going into the crisis facilitated bank participation in the PPP. For example, Barraza et al. (2020) note that lenders that were already certified as SBA 7(a) banks prior to the launch of the PPP were automatically eligible for the program. Lenders who were not previously certified were eligible subsequent to filing a SBA Lender Agreement form 3506. Studies to date have shown that PPP lending was greater in areas that were more served by the SBA in 2019 (Liu and Volker, 2020) and bore little relation to economic conditions prevailing under COVID (Granja et al., 2022).

Our identification strategy requires that prior interactions with the SBA only affected growth in lending over our sample period through its influence on participation in the PPP and PPPLF. This instrument $SBA2019_i$ is specified as the ratio of SBA lending by bank i to total bank i small business and farm lending, which satisfies

$$SBA2019_i = \frac{SBA_i}{BUSF_i}, \quad (5)$$

where SBA_i represents bank i lending through the SBA and $BUSF_i$ represents total small business and farm lending by bank i, both at year-end 2019.

As our second and third instruments, we use indicators of familiarity with the Federal Reserve discount window, which administered the PPPLF. These variables were used by Anbil et al. (2021) as instruments for the pledging of PPP loans to the PPPLF. As discussed by the authors, the practice of pledging standard loan collateral and obtaining discount window loans entails substantive interactions with the Federal Reserve. For example, banks are required to demonstrate that the Federal Reserve will be able to establish a claim on pledged loans and must submit a monthly update on any changes in their value. This process is nearly identical to that of pledging PPP loans to the PPPLF.

As discussed above, we consider a bank's decision to issue a PPP loan as dependent on its perceived probability that the loan can be converted into cash by submitting it as collateral to the PPPLF. As such, we expect that these instrumental variables will likely influence both PPP and PPPLF participation. We utilize two measures that were obtained from proprietary Federal Reserve data: a count of documents on file for a bank at the discount window ($COUNT_i$) and the total collateral pledged to the discount window program ($COLLATERAL_i$).[7] Again, we use pre-pandemic measures for these instruments, with both values calculated at year-end 2019.

[7] Please note that this data is not publicly available.

4. Results

4.1. PPP participation and lending growth

Our base specification results for the effects of PPP participation on small business and farm lending are shown in Table 3. Column 1 shows our base IV specification, with the endogenous variable PPP instrumented as described in the previous section and standard errors clustered by size. This variable enters positively and significantly at more than a 1% confidence level. Our point estimates also indicate that these programs have had economically meaningful impacts on SME lending. Combined with summary statistics in Table 2, they imply that a one standard deviation increase in PPP is associated with a 32.0 percentage point increase in small business and farm lending growth over our sample period.

We also evaluate the strength of our instruments. We ran the AR Wald weak instrument test and obtained a p-value of 0.00, and a Stock-Yogo statistic of 22.22, which passes the 13.91 critical value for a 5% confidence level to reject weak identification. As the PPP and $PPPLF$ variables are truncated on the unit interval, we report TOBIT estimation results for the first stage of our specification, available in our online appendix. All three instruments enter positively and significantly in the TOBIT regressions, without the other conditioning variables included, although with the full set of conditioning variables, $COLLATERAL$ loses its significance (Column 5).

In terms of our conditioning variables, we obtain positive and significant results at the 5% and 1% confidence levels respectively for $INDMIX$ and $TCAP$, indicating that banks with a similar industry mix to that of the SBA and banks that were better-capitalized experienced higher small business and farm lending growth. In contrast, we obtain a significantly negative coefficient estimate for $COMMITMENT$, our measure of outstanding loan commitments, and $\Delta DEPOSITS$, our measure of growth in bank core deposits.

The result for $COMMITMENT$ is intuitive since, holding all else equal, we would expect that banks with greater unused loan commitments would be called upon during this period to extend more credit to large businesses who are more prevalent in lending commitment arrangements. This would leave less funds available for lending to small business and farms. The negative coefficient estimate on the change in core deposits is somewhat surprising, but may reflect that banks with larger increases in core deposits had excess liquidity, all else equal, and responded by increasing overall lending. As small firms were more distressed at this time, this increase in overall lending was likely biased towards large firms, resulting in a decline in the share of small business and farm lending. $LIQUIDITY$ enter positively, as would be expected, but is only significant at the 11.1% confidence level. $DEPOSITS$, levels of core deposits, are insignificant.

Lastly, our indicator variables for small and medium-sized banks both enter positively, while our constant term enters negatively. This implies lower SME lending growth among large banks over this period. Moreover, our standard deviation estimates are also sufficiently small to infer that SME lending growth was higher for small banks than for medium-sized banks.

Column 2 reports our results using the control function method to address the likely endogeneity issues with our PPP variable of interest. As expected, these results are almost identical to those under two-stage least squares estimation, with the PPP entering positive and significant with an identical point estimate. The additional PPP_res residual term enters negatively at a 10% confidence level.

To demonstrate that our results are not driven by our IV estimation and choice of instruments, column 3 repeats our specification using ordinary least squares estimation, with standard errors again clustered by size. While the coefficient value on our variable of interest PPP is smaller than under our IV specification, it continues to enter significantly positive. Our conditioning variables are also qualitatively similar to those in our IV specification, with all conditioning variable point estimates entering with similar signs. However, the $CAPRAT$ and $COMMITMENT$ variables lose their statistical significance under OLS estimation.

Table 3
PPP as a determinant of lending growth.

	(1) IV	(2) Control	(3) OLS	(4) SM/MED banks	(5) LG banks
PPP	1.216***	1.216***	0.897***	1.222***	1.195**
	(0.0151)	(0.0364)	(0.0172)	(0.00958)	(0.420)
INDMIX	0.375**	0.374	0.720*	0.394**	0.127
	(0.133)	(0.170)	(0.110)	(0.139)	(1.221)
LIQUIDITY	0.0945	0.0947	0.163	0.0777	0.609
	(0.0593)	(0.0714)	(0.0457)	(0.0672)	(1.090)
DEPOSITS	−0.0246	−0.0252	−0.141	0.0107	−0.667
	(0.0487)	(0.0447)	(0.0349)	(0.0456)	(0.603)
CAPRAT	0.462***	0.461*	0.199	0.505***	−0.0646
	(0.0556)	(0.0721)	(0.0619)	(0.0154)	(1.271)
COMMITMENT	−1.203***	−1.203*	−0.0435	−1.347***	−0.229
	(0.227)	(0.192)	(0.0207)	(0.229)	(0.763)
Δ DEPOSITS	−0.409***	−0.409**	−0.859***	−0.409***	−0.686
	(0.0315)	(0.0200)	(0.0180)	(0.0330)	(1.329)
SMALL	0.0941***	0.0942*	0.0514**	0.0371***	
	(0.00727)	(0.0149)	(0.00226)	(0.00131)	
MED	0.0542***	0.0543*	0.0583***		
	(0.00585)	(0.00754)	(0.000684)		
PPP_res		−0.296*			
		(0.0337)			
Constant	−0.164***	−0.164	0.0478	−0.138***	0.315
	(0.0339)	(0.0410)	(0.0441)	(0.0288)	(0.593)
Observations	4456	4456	4719	4329	127
R^2	0.410	0.438	0.439	0.409	0.341

Note: The dependent variable is $\Delta BUSF$, growth in small businesses and farm lending from 2019.Q4 through 2020.Q2. PPP is the ratio of a bank's PPP participation to small business and farm lending; $INDMIX$ is our measure of industry mix in SBA loans in 2019; $LIQUIDITY$ is a bank's total liquidity in 2019.Q4; $DEPOSITS$ is its total deposits in 2019.Q4; $CAPRAT$ represents its total capital ratio; $COMMITMENT$ is its unused commitments in 2019.Q4; $\Delta DEPOSITS$ is the change in its deposits from 2019.Q4 and 2020.Q2; and $SMALL$ and MED are indicator variables for small and medium-sized banks, respectively. Columns 1, 4, and 5 are instrumental variable regressions. Column 2 is the control function regression; PPP_res is the residual used for the control function specification. Column 3 is an OLS regression. Column 4 represents the sample of small and medium-sized banks. Column 5 represents the sample of large banks. Standard errors in parentheses are clustered by bank size.

Large banks enjoyed a potential advantage in increasing lending under the PPP program because most had electronic platforms already in place, allowing them to capitalize on the first-come, first-served format of the PPP. We therefore investigate the robustness of our results to this potential heterogeneity by bank size by splitting the sample into one containing our small and medium-sized banks and the other containing the large banks in our sample, again under our IV estimation with the same instruments. Our results are reported in columns 4 and 5. Column 4, which reports the results for the first sub-sample, adds a small bank indicator to distinguish between average small and medium bank lending growth.

For both sub-samples, our coefficient estimate for the variable of interest, PPP, is positive and statistically significant at a 1% confidence level. Point estimates for this variable of interest are roughly the same as those in our base sample for both sub-samples. However, the standard deviation for the large bank sub-sample is higher, with the net result that our point estimates indicate a higher increase in bank lending growth for a one-standard deviation increase in PPP for the large bank sub-sample, 40.0 percentage points vs. 31.2 percentage points. The small bank fixed effect in the first sub-sample is positive and significant, with our coefficient point estimate suggesting that small business and farm lending growth was close to four percentage points higher on average for small banks than for medium-sized banks.

4.2. PPPLF participation and lending growth

Our base specification results for the implications of PPPLF participation for SME lending are shown in Table 4. Column 1 again displays our base IV specification, with the endogenous variable $PPPLF$ instrumented as described in the previous section and standard errors clustered by size. This variable enters positively and significantly at more than a 1% confidence level. Our point estimates also indicate that the PPPLF had an economically meaningful effect on SME lending. Combined with summary statistics in Table 2, they imply that a one standard deviation increase in $PPPLF$ is associated with a 33.1 percentage point increase in small business and farm lending growth over our sample period.

To evaluate the strength of our instruments, we ran the AR Wald weak instrument test and obtained a p-value of 0.00 and a Stock-Yogo statistic of 22.22, which passes the 13.91 critical value for a 5% confidence level to reject weak identification. As the PPP and $PPPLF$ variables are truncated on the unit interval, we report TOBIT estimation results for the first stage of our specification in Appendix Table A.1. All three instruments enter positively and significantly in the TOBIT regressions, without the other conditioning variables included, although with the full set of conditioning variables, $COLLATERAL$ loses its significance for PPP and is only statistically significant at a 10% confidence level for $PPPLF$ (Columns 5 and 6). In addition, the sign of the coefficient point estimate on $SBA2019$ becomes negative under TOBIT with the full set of conditioning variables (Column 6).

Our conditioning variables appear to enter with more precision here. We again obtain positive and significant results at 5% and 1% confidence levels, respectively, for $INDMIX$ and $TCAP$. However, all of the other conditioning variables also enter positive and significantly at a 5% confidence level, with the sole exception of $\Delta DEPOSITS$, which enters positively at a 10% confidence level. The $SMALL$ variable now enters negatively, while the MED variable continues to enter positively, but is now insignificant.

Our control function specification (column 2) again enters with coefficient point estimates roughly consistent to those in our base IV specification. However, p-values are reduced, so that in particular PPP misses statistical significance, entering at a 12.6% confidence level. We also repeat our specification under ordinary least squares in column 3. The coefficient point estimate is much reduced, but still enters positively at a 10% confidence level.

Finally, we again separate our sample into two size categories and report the results for our base specification under IV in columns 4 and 5, respectively. Our coefficient estimate for the variable of interest, $PPPLF$, is positive and statistically significant at a 1% confidence level for the small and medium-sized bank sub-sample (column 4). Our point estimate indicates that a one-standard deviation increase in the share of PPP loans used in the PPPLF as collateral would be associated with a 34.1 percentage point increase in small business and farm lending growth on average.[8] However, our coefficient estimate for $PPPLF$ for the large bank sub-sample is smaller and statistically insignificant. Our point estimate indicates that a one-standard deviation increase in $PPPLF$ within the large bank sub-sample would be associated with a more modest 25.6 percentage point increase in small business and farm lending growth.

Overall, our results indicate that participation in the PPPLF program was associated with substantively higher small business and farm lending growth. However, our sub-samples indicate that the program was more important as a source of lending growth for small and medium-sized banks than it was for large banks. This result is consistent with the perception that small banks were particularly reliant on the PPPLF as a vehicle to participate in the PPP without placing undesirable pressure on their overall liquidity positions.

[8] The mean of PPPLF participation is actually higher at 0.116 for large banks, as opposed to 0.087 for small and medium-sized banks. The standard deviations for these sub-sample distributions are 0.295 and 0.250 for large- vs small and medium-sized banks, respectively.

Table 4
PPPLF as a determinant of lending growth.

	(1) IV	(2) Control	(3) OLS	(4) SM/MED banks	(5) LG banks
PPPLF	1.315***	1.317	0.175*	1.365***	0.867
	(0.301)	(0.518)	(0.0400)	(0.232)	(1.526)
INDMIX	0.764***	0.760*	1.418*	0.844***	−1.354
	(0.0810)	(0.152)	(0.288)	(0.0397)	(1.827)
LIQUIDITY	0.704***	0.705	0.534*	0.734***	−0.878
	(0.149)	(0.178)	(0.106)	(0.126)	(1.112)
DEPOSITS	0.464**	0.464	−0.448***	0.402**	1.537
	(0.158)	(0.385)	(0.0114)	(0.140)	(3.744)
CAPRAT	0.962**	0.968	−0.120	0.917**	0.966
	(0.364)	(0.545)	(0.0723)	(0.342)	(3.885)
COMMITMENT	1.098***	1.097*	1.474*	1.016***	1.584
	(0.152)	(0.139)	(0.299)	(0.145)	(0.888)
Δ DEPOSITS	1.787*	1.786	−1.799***	1.977***	−0.507
	(0.748)	(1.546)	(0.0564)	(0.471)	(4.260)
SMALL	−0.141***	−0.141	−0.205*	−0.141***	
	(0.0268)	(0.0490)	(0.0216)	(0.00916)	
MED	0.00285	0.00278	−0.0300		
	(0.0153)	(0.0271)	(0.0132)		
PPPLF_res		−1.155			
		(0.489)			
Constant	−0.282	−0.283	0.753**	−0.227	−0.935
	(0.235)	(0.492)	(0.0492)	(0.200)	(3.691)
Observations	4073	4073	4074	3960	113
R^2	.	0.181	0.176	.	.

Note: The dependent variable is $\Delta BUSF$, growth in small businesses and farm lending from 2019.Q4 through 2020.Q2. $PPPLF$ is the ratio of a bank's borrowing from the PPPLF program to its PPP lending; $INDMIX$ is our measure of industry mix in SBA loans in 2019; $LIQUIDITY$ is a bank's total liquidity in 2019.Q4; $DEPOSITS$ is its total deposits in 2019.Q4; $CAPRAT$ represents its total capital ratio; $COMMITMENT$ is its unused commitments in 2019.Q4; $\Delta DEPOSITS$ is the change in its deposits between 2019.Q4 and 2020.Q2; and $SMALL$ and MED are indicator variables for small and medium sized banks, respectively. Columns 1, 4, and 5 are instrumental variable regressions. Column 2 is the control function regression; PPP_res is the residual used for the control function specification. Column 3 is an OLS regression. Column 4 represents the sample of small and medium-sized banks. Column 5 represents the sample of large banks. Standard errors in parentheses are clustered by bank size.

4.3. Small business and farm lending growth separately

Table 5 repeats our base specification with our dependent variable changed to separate measures of small business lending growth (columns 1 and 2) and small farm lending growth (columns 3 and 4). Both of our variables of interest, PPP and $PPPLF$, enter positively and significantly, with coefficient point estimates similar to those for our base specification for growth in aggregate SME lending. Our results for the conditioning variables are also similar to those in our base specifications for both variables of interest.

However, our results for small farm lending growth alone are quite different. Columns 3 and 4 show that PPP and $PPPLF$ enter insignificantly with a negative point estimate. These results suggest that while participation in the PPP and PPPLF programs enhanced small business growth during the COVID crisis, it was not associated with growth in small loans to farms. Indeed, the negative coefficient point estimates we obtain for both PPP and $PPPLF$ suggest that there may even have been some adjustment by banks away from farm lending in response to perceived enhanced lending opportunities to small businesses under the PPP and PPPLF programs.

These results were likely driven by restrictions on PPP loans at the outset of the program, as discussed in Section 2. Initially, PPP loans could only be extended to small farms if they had reported a positive net profit on their income taxes for 2019. This requirement kept many farms from applying for PPP assistance, as was widely reported in the agricultural press. The requirement was changed in December 2020 to permit farms with positive gross income to apply for PPP loans.

Table 5
Small business and farm lending growth only.

	(1) Sm businesses	(2) Sm businesses	(3) Farms	(4) Farms
PPP	0.956***		−0.0734	
	(0.0108)		(0.0752)	
PPPLF		1.210***		−0.234
		(0.287)		(0.142)
INDMIX	0.523***	0.590***	−0.255	−0.194
	(0.102)	(0.0658)	(0.331)	(0.154)
LIQUIDITY	0.00315	0.592***	0.0287	−0.0349
	(0.0513)	(0.140)	(0.0481)	(0.0600)
DEPOSITS	−0.0993	0.401***	0.0493	−0.113
	(0.0695)	(0.110)	(0.0623)	(0.125)
CAPRAT	0.253***	0.889**	0.0269	−0.160
	(0.0386)	(0.345)	(0.193)	(0.110)
COMMITMENT	−0.672***	0.991***	0.244	0.109
	(0.185)	(0.143)	(0.218)	(0.108)
Δ DEPOSITS	−0.772***	1.512*	−0.113	−0.778
	(0.0165)	(0.735)	(0.126)	(0.475)
SMALL	0.0890***	−0.0974***	−0.0507**	−0.0541***
	(0.0104)	(0.0273)	(0.0184)	(0.0121)
MED	0.0681***	0.0208	−0.0353***	−0.0419***
	(0.00688)	(0.0162)	(0.00655)	(0.00612)
Constant	0.0468	−0.176	0.0146	0.181
	(0.0389)	(0.190)	(0.0986)	(0.133)
Observations	4328	3962	3663	3415
R^2	0.399	.	.	.

Note: The dependent variable in the first two columns is ΔBUS, growth in small business lending from 2019.Q4 through 2020.Q2. The dependent variable in last two columns is $\Delta FARM$, growth in small farm lending from 2019.Q4 through 2020.Q2. PPP is the ratio of a bank's PPP participation to its small business and farm lending; $PPPLF$ is the ratio of its borrowing from the PPPLF program to its PPP lending; $INDMIX$ is our measure of industry mix in SBA loans in 2019; $LIQUIDITY$ is a bank's total liquidity in 2019Q4; $DEPOSITS$ is their total deposits in 2019.Q4; $CAPRAT$ represents its total capital ratio; $COMMITMENT$ is its unused commitments in 2019.Q4; $\Delta DEPOSITS$ are the change in deposits between 2019 Q4 and 2020 Q2; and $SMALL$ and MED are indicator variables for small and medium-sized banks, respectively. All columns are instrumental variable regressions. Standard errors in parentheses are clustered by bank size.

5. Robustness checks

We next summarize further robustness checks of our base specification results, also available in our online appendix at https://www.frbsf.org/wp-content/uploads/sites/4/wp2021-10_appendix.pdf. We first consider a variety of changes to our base specification. In addition to the specification with both PPP and $PPPLF$ included simultaneously discussed above, we consider lagged bank lending growth and levels, to account for potential trends in SME lending that may spuriously interact with individual banks' intensity of PPP and PPPLF participation. We add lagged SME lending growth, measured as growth in small business and farm lending from 2019.Q2 to 2019.Q4, and lagged levels of small business and farm lending, measured as total lending for 2019. We add these variables both individually and in tandem. Our results show that our base specification results are robust to all of these inclusions, as PPP and $PPPLF$ both continue to enter positively and significantly with similar point estimates.

We also substitute the tier1 risk-adjusted capital ratio for the total capital ratio. Our qualitative results are again robust to this perturbation.

We also consider the $INDMIX$ variable as an additional instrument, rather than as a stand-alone explanatory variable. Including this variable as an instrument requires the additional assumption that the influence of $INDMIX$ affects lending growth only through its encouragement of additional PPP or PPPLF participation. In this specification, both the PPP and $PPPLF$ variables enter positively and significantly with larger coefficient point estimates than those in our base specification, suggesting that our results are robust to this alternative specification.

We also entertain different estimation methodologies. We first consider a variety of standard errors, including heteroscedasticity-robust standard errors, conventional standard errors, and clustering by geographic regions instead of by bank size. Our results are robust to all of these changes, as both variables of interest PPP and $PPPLF$ continue to enter positive and significantly at 1% confidence levels. We also consider a weighted-least squares specification, with observations weighted by the intensity of bank participation in small business and farm lending. Our results for PPP are again robust to this alternative specification, while $PPPLF$ is insignificant. The contrast of these results with those in our unweighted base specification suggests that the impact of the PPPLF was not significantly different between banks that were and were not extensive SME lenders prior to the pandemic.

We also consider alternative outlier treatments. We winsorize our conditioning variables at wider and narrower levels, which adjust for differing sets of outliers. Both PPP and $PPPLF$ continue to enter positively and significantly with coefficient estimates of similar magnitudes, except for the case of no winsorization, for which the PPP variable enters insignificantly. We also truncate the variables rather than winsorizing, and again the PPP and $PPPLF$ variables entering as positive and at statistically significant levels.

6. Program effects on non-PPP lending

As mentioned above, there is a debate about whether the PPP truly led to increased SME lending, or if it merely resulted in banks designating loans that would have been extended anyway as PPP loans to take advantage of government guarantees and of potential liquidity advantages from using these loans as collateral under the PPPLF program. Berger et al. (2021a) found that lending terms for firms with pre-existing banking relationships tightened at the onset of the pandemic, providing perhaps some rationale for the observed reduction in non-PPP borrowing by smaller firms. In particular, while Karakaplan (2022) identifies complementarities between PPP and non-PPP SME lending, Chodorow-Reich et al. (2022) find that PPP and conventional borrowing were substitutes in the subset of very large banks covered in the Federal Reserve's Y-14 dataset.

We pursue this question here, based on movements in banks' SME lending conducted outside of the PPP or PPPLF programs. While it is not clear that movement in such loans provides a clear indication of the effect of the PPP on overall lending, it seems likely that some may interpret the program as "more successful" if more intensive participation was not associated with a decline in what we characterize as "non-PPP" small business and farm lending.

We identify the subset of small business and farm lending in the first half of 2020 that was not connected to the PPP as "non-PPP" lending. Then, since the PPP did not exist in 2019, we define growth in non-PPP lending in 2020 as the difference between non-PPP small business and farm lending at the end of 2020.Q2 with total small business and farm lending in 2019. By this definition, small business and farm lending grew by 32.1% over the period on average across banks, while growth in non-PPP lending was −2.6% on average. These headline numbers suggest that substantial substitution did take place, in the sense that loans that might have been extended in the absence of these program were instead placed under the PPP program to access government guarantees. Of course, our approach can only speak to the implications of the program on the relative growth in small business and farm lending, and we do so by regressing our definition of growth in non-PPP lending in the same IV specification that we use in our base specification.

Our results are shown in Table 6. Columns 1 and 2 show that for our full-sample, non-PPP small business and farm lending growth does decline with greater participation in both the PPP and the PPPLF program. However, this result by no means implies that the programs

Table 6
Non-PPP lending.

	(1) Full	(2) Full	(3) SM/MED banks	(4) SM/MED banks	(5) LG banks	(6) LG banks
PPP	−0.105***		−0.100***		−0.0226	
	(0.00800)		(0.00503)		(0.0241)	
PPPLF		−0.0774***		−0.0709***		−0.0502
		(0.00686)		(0.00772)		(0.0888)
INDMIX	0.0513***	−0.00424	0.0504***	−0.00606	−0.0219	0.0488
	(0.0106)	(0.00301)	(0.0124)	(0.00524)	(0.0700)	(0.106)
LIQUIDITY	0.0100***	−0.0353***	0.00939***	−0.0378***	0.0694	0.111
	(0.00212)	(0.00461)	(0.00184)	(0.00132)	(0.0625)	(0.0647)
DEPOSITS	0.0142**	0.00451	0.0154***	0.0173***	−0.0410	−0.187
	(0.00532)	(0.0122)	(0.00369)	(0.00191)	(0.0346)	(0.218)
CAPRAT	−0.0437***	−0.0292	−0.0378***	−0.00955	−0.112	−0.184
	(0.00981)	(0.0191)	(0.00416)	(0.0122)	(0.0729)	(0.226)
COMMITMENT	−0.161*	−0.397***	−0.208***	−0.437***	0.0141	−0.00666
	(0.0638)	(0.0509)	(0.0307)	(0.0155)	(0.0437)	(0.0517)
Δ DEPOSITS	0.357***	0.297***	0.369***	0.320***	−0.0228	−0.122
	(0.0593)	(0.0470)	(0.0528)	(0.0388)	(0.0761)	(0.248)
SMALL	−0.0338***	−0.0170***	−0.0182***	−0.00424***		
	(0.00174)	(0.00269)	(0.000681)	(0.000261)		
MED	−0.0156***	−0.0137***				
	(0.000961)	(0.00146)				
Constant	0.0371***	0.0144	0.0200***	−0.0105*	0.0327	0.147
	(0.00731)	(0.00796)	(0.00470)	(0.00472)	(0.0340)	(0.215)
Observations	4463	4083	4336	3970	127	113
R^2	0.364	0.147	0.374	0.171	0.240	.

Note: The dependent variable is growth in non-PPP small businesses and farm lending from 2019.Q4 through 2020.Q2. Columns 1 and 2 are based on the full sample of banks. Columns 3 and 4 are based on the sample of small and medium-sized banks. Columns 5 and 6 are based on the sample of large banks. PPP is the ratio of a bank's PPP participation to small business and farm lending; $PPPLF$ is ratio of borrowing from the PPPLF program to PPP lending; $INDMIX$ is our measure of industry mix in SBA loans in 2019; $LIQUIDITY$ is a bank's total liquidity in 2019.Q4; $DEPOSITS$ is its total deposits in 2019.Q4; $CAPRAT$ represents its total capital ratio; $COMMITMENT$ is its unused commitments in 2019.Q4; $\Delta DEPOSITS$ is the change in its deposits from 2019.Q4 and 2020.Q2; and $SMALL$ and MED are indicator variables for small and medium-sized banks, respectively. All columns are instrumental variable regressions. Standard errors in parentheses are clustered by bank size.

discouraged "normal" lending. Instead, it more likely implies that some amount of lending that would have taken place anyway was placed under the PPP and PPPLF programs to obtain the offered guarantees and liquidity advantages of these programs.[9]

Our analysis also identifies a discrepancy in the impact of these programs on large- versus small and medium-bank lending. Our results for small and medium-sized banks are shown in columns 3 and 4, while our results for our large bank sub-sample are shown in columns 5 and 6. Our finding of negative coefficients on the program variables appears to be completely driven by the small and medium-sized banks in our sample, which obtain statistically significant negative coefficient estimates for both PPP and PPPLF participation, with point estimates roughly the same as those we obtain for our full sample. However, the coefficient estimates for the large bank sub-sample are very insignificant. We interpret these results as suggesting that large bank lending outside the PPP program was relatively independent of the program itself. This interpretation appears plausible, as the PPP and especially the PPPLF, would have only modest implications for large bank balance sheets. In contrast, it appears that the small and medium-sized banks did indeed substitute their small business and farm lending towards both programs in response to the incentives provided. As a result, our measured non-PPP SME lending was found to be significantly decreasing in participation in both programs.

7. Conclusion

We find that increased bank participation in the PPP and the PPPLF programs both substantively encouraged growth in SME lending at the outset of the pandemic period. Our regression estimates suggest that on average a one standard deviation increase in PPP participation is associated with a 32.0 percentage point increase in SME lending growth relative to year-end 2019, while a one standard deviation increase in PPPLF participation appears to lead to a similarly large increase of 33.0 percentage points in SME loan growth.

We also identify important differences by bank size. While the sensitivity of lending growth to participation in the PPP program was roughly equal across all banks, there was a large discrepancy by size in the importance of the PPPLF program. We identify a positive and significant role for lending growth in PPPLF participation among small and medium-sized banks, but an insignificant role for that program among large banks. This finding is intuitive, as large bank liquidity was likely less sensitive to SME lending levels. As such, our findings support claims (e.g., Bowman (2020)) that the PPPLF played a special role in increasing PPP participation among small and medium-sized banks.

Our results also contribute to the debate concerning whether these two programs encouraged additional SME lending, or merely resulted in a repurposing of SME loans that would have been made anyway. Our analysis shows that while overall SME lending grew with participation in both PPP programs, non-PPP SME lending growth declined. However, that decline is completely driven by the small and medium-sized banks in our sample. We interpret these results as suggesting that while we do observe some substitution of small business lending into the PPP

[9] Our empirical approach differs from Karakaplan (2022) in a number of dimensions, leaving it challenging to attribute our contrasting results (and those in Chodorow-Reich et al. (2022)) to any individual source. However, one important distinction is our use of IV estimation to deal with the likely endogeneity of the SME bank lending response to program participation. However, we continue to obtain a statistically significant negative coefficient estimate for the PPP variable in non-PPP lending when we run our specification under OLS.

program by small and medium-sized banks, the PPP program did not appear to affect non-PPP lending by large banks.

Finally, we leave for future work consideration of the implications of the PPP and PPPLF for bank vulnerability. We offer some preliminary results on this issue in the online appendix, which examines the implications of participation in both programs for changes in bank capital ratios. Our results indicate that while total bank capital ratios declined with increased participation in both programs, that was not the case for risk-adjusted tier-1 capital ratios, which account for the fact that the PPP loans were government guaranteed. Indeed, our point estimates indicate that a one standard deviation increase in PPP and PPPLF participation was associated over our sample period with substantial 13.3 and 25.8 percentage point increases in growth in tier 1 risk-adjusted capital ratios. Of course, this risk was not lost, but instead transferred to the government guarantees extended under the PPP program.

CRediT authorship contribution statement

Jose A. Lopez: Conceptualization, Formal analysis, Data curation. **Mark M. Spiegel:** Conceptualization, Formal analysis, Data curation.

Data availability

The data that has been used is confidential.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jfi.2022.101017.

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