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PERSISTENT EFFECTS OF THE PAYCHECK PROTECTION PROGRAM AND THE PPPLF ON SMALL BUSINESS LENDING

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ABSTRACT. Using bank-level U.S. Call Report data, we examine the longer-term effects of the Paycheck Protection Program (PPP) and the PPP Liquidity Facility on small business (SME) lending. Our sample runs through the end of 2023H1, by which time almost all PPP loans were forgiven or repaid. To identify a causal impact of program participation, we instrument based on historical bank relationships with the Small Business Administration and the Federal Reserve discount window prior to the onset of the pandemic. Elevated bank participation in both programs was positively associated with a substantial cumulative increase in small business lending growth. However, we find a negative impact of both programs during the final year of our sample, suggesting that the increase may not prove permanent. Our results are driven by the small and medium-sized banks in our sample, which are not stress-tested and hence not included in Y-14 banking data, illustrating the importance of considering small and medium-sized banks in evaluating the performance of SME lending programs.

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I. Introduction

The Paycheck Protection Program (PPP) was created by the U.S. Congress to assist small businesses during the COVID-19 pandemic in retaining employees and covering their expenses. Small businesses (SMEs) were particularly exposed to disruptions from pandemic-related lockdowns due to their heavy involvement in service sectors, including retail and food services (Bowman (2020)). The program was administered by the Small Business Administration (SBA) and allowed qualified small businesses to obtain "forgivable" loans from commercial banks and other financial institutions. To encourage commercial banks to participate in the PPP program, the Federal Reserve established the Paycheck Protection Program Liquidity Facility (PPPLF), which allowed banks to lend through the PPP program without adverse consequences for balance sheet liquidity. Under the PPPLF, banks could use PPP loans as risk-free collateral for Federal Reserve borrowing.[1]

The PPP program was very large, with close to $793 billion dollars of funds extended in total. At the time of this writing, over $762.4 billion worth, have been forgiven (Committee (2024)).[2] However, the program was highly controversial, as analysts argued that the involvement of commercial banks distorted the allocation of funds. Moreover, the employment benefits of the program ending up modest relative to its cost (e.g. Granja et al. (2022)).[3] Studies also indicate that the majority of funds extended went to business owners and shareholders, rather than employees (e.g. Autor et al. (2022)). Indeed, Autor et al. (2022) acknowledges that the desire to distribute funds quickly, combined with the involvement of the private sector through direct commercial bank lending, likely led to the distribution of PPP funds being poorly correlated with the intensity of distress, as proxied by the correlation of economic activity and funds received geographically. Still, Bartik et al. (2020) show that given sufficiently costly delay of distributing funds, even programs with poor targeting outcomes can improve welfare.

Despite these concerns about the distribution of funds, a large literature has shown that the PPP and PPPLF programs did succeed in encouraging immediate expansion of overall SME lending during the pandemic (e.g. Beauregard et al. (2020), Hubbard and Strain (2020), Li and Strahan (2021), Anbil et al. (2023), Lopez and Spiegel

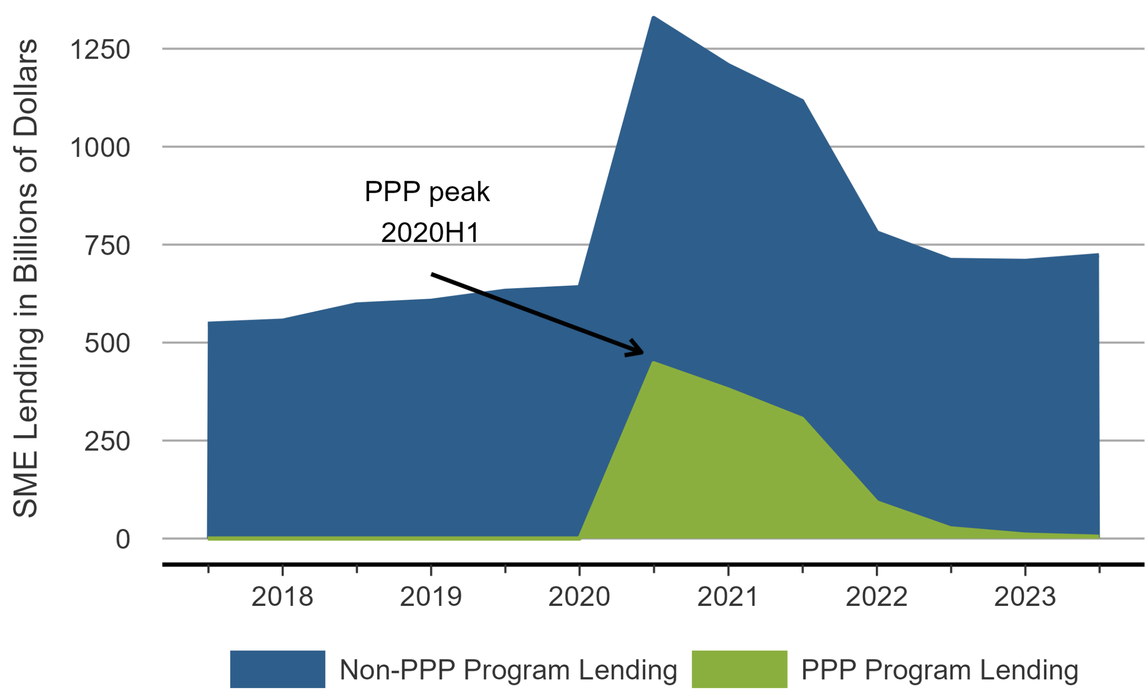
[1] See Anbil et al. (2023) for a review of the details of the PPPLF.

[2] Data as of October 2023. As of that date, 10.6 million of the 11.5 million loans extended under the PPP program had been forgiven.

[3] Other studies disagree. For example, Joaquim and Netto (2021) estimate that the program saved 7.5 million jobs.

(2023), and Marsh and Sharma (2024)). Moreover, Joaquim and Wang (2022) show that receiving PPP loans improved firm financial conditions during the pandemic.

Figure 1. Total Small Business Bank Lending 2017H1-2023H1



Note: Total SME lending and PPP program lending is split by PPP and non-PPP loans.

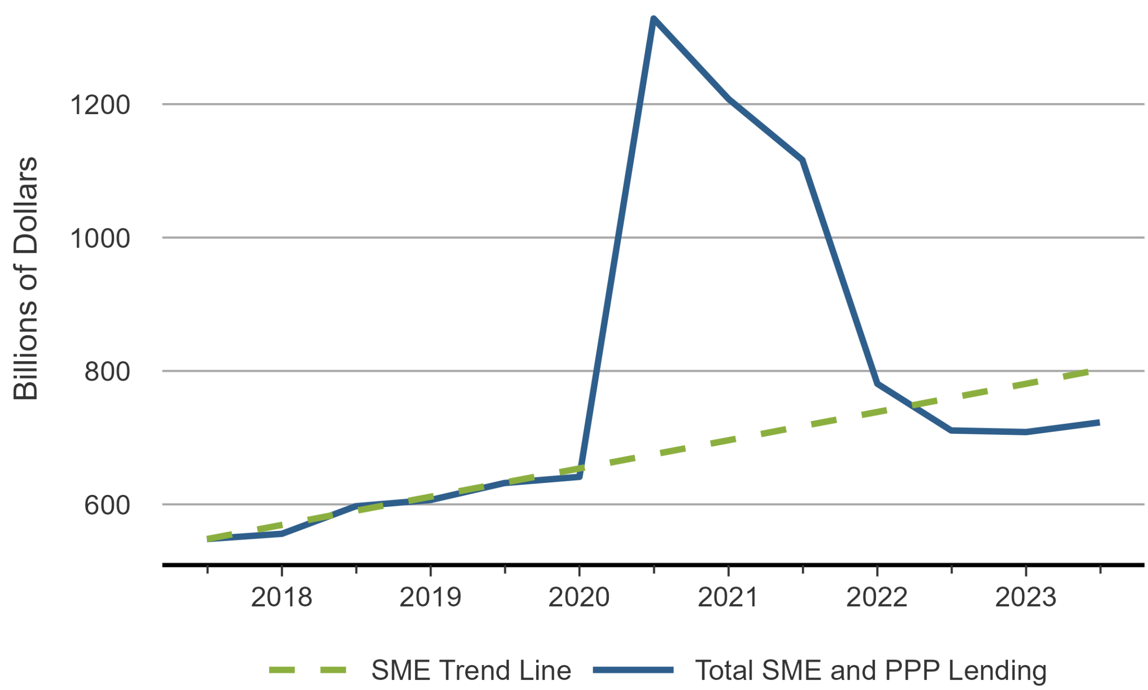
The positive impact of the PPP on lending can be seen in Figure 1. Figure 1 shows total commercial bank PPP and regular small business lending, as reported in regulatory filings in the Call Report, from the end of 2017H1 through the end of 2023H1.[4] It can be seen that lending to small businesses grew dramatically during the pandemic. Going into the pandemic at the end of 2019, total small business lending had grown to 641 billion dollars. It then increased markedly with the onset of the pandemic and the commencement of PPP lending, reaching a peak at the end of the first half of 2020. Approximately 1,300 banks also participated in the PPPLF at that time, with close to 15% of outstanding PPP loans being pledged as collateral [Lopez and Spiegel (2023)]. However, the outsized growth over this period is not limited to PPP lending. Conventional non-PPP lending also increased. By the end of our sample, participation in both programs was close to zero, with total outstanding

[4]As discussed in the data section below, our Call Report sample is biannual, as many institutions only submit reports in the second and fourth quarters of the year.

commercial bank PPP lending reported in the Call Report having fallen from a high of over $447 billion at the end of 2020H1 to $4.6 billion at the end of 2023H1.

In this paper, we investigate whether PPP lending encouraged conventional lending to small businesses and farms (hereon referred to as SMEs) even after the program had largely ended. Despite the evidence reviewed above that commercial bank exposure to SMEs grew rapidly during the PPP program, the impact of the program on conventional SME lending is less clear. Banks that were planning on extending loans to SMEs may have preferred to substitute such lending for PPP loans in order to benefit from the guarantees offered. However, if banks and their SME borrowers forged relationships during the elevated lending period associated with the PPP program, the increased exposure to those borrowers may have persisted beyond the program itself.

Figure 2. Total Small Business Bank Lending



Note: The line representing all lending is the sum of SME and PPP lending for all banks in the Call Report for each half-year. The trend line represents average annual growth in SME lending from 2017H1 to 2019H2.

Figure 2 shows that after the termination of the PPP program, aggregate conventional commercial bank SME lending fell rapidly towards (and indeed modestly below) trend.[5] However, it is still possible that participation in the lending programs played a role in the distribution of SME lending activity across banks. Indeed, the literature on the immediate impact of the programs on conventional SME lending during the pandemic is mixed. Karakaplan (2022) finds that conventional SME business and real estate loans during the pandemic were complementary to PPP participation during the pandemic. In contrast, Chodorow-Reich et al. (2022) find using a Y-14 data sample of stress-tested large banks that PPP and conventional SME lending behaved as substitutes.

We investigate the longer-term impact of participation in these programs on SME lending using bank-level Call Report data up to the midpoint of 2023. At that point, almost all PPP debt had been repaid, or in most cases, forgiven.[6] As reporting to the Call Report is compulsory for all US banks, our study includes small and medium-sized banks not included in the sample of stress-tested larger banks in Y-14 data. As shown below, these small and medium-sized banks are important sources of SME lending.

Our dependent variable is the average annual percentage growth in SME lending from 2019H2 through 2023H1. Our variable of interest in our base specification is the share of PPP lending in bank assets in 2020H1, the peak period of PPP exposure in our sample. While additional funds were extended in the second half of 2020 and the first half of 2022, we concentrate on the first tranche of lending, as net changes in PPP lending data after that represent a mix of new disbursements and reductions for paid or forgiven existing PPP loans.

To deal with the likely endogeneity of participation of both the PPP and the PPPLF programs, we follow Anbil et al. (2023) and Lopez and Spiegel (2023) in instrumenting for participation in both programs based on existing ties to both the Small Business Administration (SBA) and the Federal Reserve prior to the onset of the pandemic.[7] Greater exposure to the SBA prior to the crisis likely facilitated participation in the PPP program, as banks that were certified as SBA7(a) lenders were automatically eligible for the PPP upon launch. Moreover, this instrument is likely to be informative,

[5]As discussed in the data section below, aggregate lending is obtained from the FFIEC Call Report at half-year frequency.

[6]Because many PPP loans had 5 year maturities, banks did have modest residual PPP exposure at the end of 2023H1 of 6.62 billion dollars. However, this value pales in comparison with the 447 billion dollars of PPP extension at our sample peak at the end of 2020H1.

[7]Humphries et al. (2020) show that superior awareness concerning the PPP program among firms also resulted in more success in obtaining funds through the program.

as PPP lending was greater in areas that were more served by the SBA in 2019 (see Liu and Volker (2020)), and our posited exclusion restrictions are likely to be valid as the geographic patterns of PPP lending was greater in areas that were more served by the SBA (e.g. Liu and Volker (2020)) and less correlated with the economic conditions under the pandemic (Granja et al. (2022)). We consider two indicators: The share of bank SBA lending and the similarity of bank industry lending shares to the lending portfolio of the SBA, both measured prior to the onset of the pandemic.

We also consider indicators of preparedness for Federal Reserve discount window borrowing. The Federal Reserve also administered the PPPLF program, and so additional preparedness for discount window borrowing is likely to have left a bank better-prepared to capitalize on guaranteed funds through the PPP program without jeopardizing their liquidity positions. We use the number of documents on file for a bank at the discount window, as well as total collateral pledged to the discount window program, with both values calculated at year-end 2019. These variables likely were correlated with both PPP and PPPLF participation, as the perceived ease with which funds extended through the PPP could be converted into cash through the PPPLF should have encouraged bank participation in the PPP as well.

Our results demonstrate that cumulative SME lending growth over the period was positively correlated with bank participation in the PPP program, even though outstanding PPP loans had fallen close to zero by the end of our sample. On average, our full-sample base specification coefficient estimates suggest that a one standard deviation increase in our PPP participation measure is associated with a 3.8 percentage point increase in average annual SME lending growth. Participation in the PPPLF program yields similar results, as our point estimates suggest that a one standard deviation increase in PPPLF participation is associated with a 4.9 percentage point increase in average annual SME lending growth over our sample period.

We also investigate discrepancies by bank size. First, we rerun our full sample PPP specification with observations weighted by bank asset size and obtain similar results to our unweighted specification. However, we find that our weighted results for the PPPLF program is insignificant. This suggests less responsiveness of large bank SME lending to PPPLF participation.

To confirm that SME lending growth by small and medium-sized banks is more responsive to both PPP and PPPLF participation than lending growth by large banks, we then separate our sample into groups of small, medium, and large bank subsamples. We identify a positive and significant relationship between PPP lending for both small and medium-sized banks, with qualitatively similar coefficient point estimates as we obtain for our full sample. However, we do not find a significant role for program participation in SME lending for large banks. We observe the same pattern for the PPPLF: Long-term growth in SME lending is found to be positively correlated with participation in the PPPLF program for small and medium-sized banks, but not for large banks. These results are in keeping with Bowman (2020), who noted that that the PPPLF was of particular importance to smaller institutions that were experiencing liquidity shortages during the pandemic, leading to challenges associated with expanding their SME lending through the PPP.

Finally, we rerun our specification for a sample beginning in 2022H1, after the funds associated with the PPP program had largely been forgiven or repaid. For this "post-program period," we find a significantly negative relationship between participation in both the PPP and PPPLF programs and SME lending growth. This suggests that the programs expanded bank exposure to SMEs beyond their long-run desired levels during the PPP program, but then moved to correct these exposures once the incentives associated with the programs were eliminated. As such, while the SME lending gains associated with the PPP and PPPLF programs appear to have been persistent, they may not prove to be permanent.

The prevailing literature on banking relationships suggests that the persistent impact of the PPP program would be limited. As discussed by Boot and Thakor (2002), banking relationships conventionally emerge as the product of costly information gathering or monitoring [e.g. Diamond (1984) and Allen (1990)]. In a recent paper, Berger et al. (2024) find that the hard and soft information gathered through conventional lending has implications for so-called "transactions lending," in this case credit card lending. As noted by Berger et al. (2024), this form of lending is largely based on externally sourced hard information alone. However, the guarantees afforded by the government under the PPP removed much of the incentive to engage in any information acquisition activity. As such, finding a persistent effect of PPP and PPPLF program participation suggests that PPP lending alone was sufficient to generate an enduring increase in SME lending, without the acquisition of costly information on individual SME borrowers.

The simultaneous large increases in PPP and conventional SME lending at the outset of the pandemic (see Figure 1) may have played a role. It appears that PPP funds alone were insufficient for the borrowing needs of some SMEs. Banks with greater PPP participation appear to have responded by increasing conventional SME loans to these borrowers as well. The persistent increase we see in the data from association with PPP and PPPLF participation may then reflect the impact of soft information gathered through the conventional SME lending activity inspired by the PPP.

The remainder of this paper is divided into seven sections. The following section gives a brief review of the details of the PPP and PPPLF programs. Section 3 discusses the data used in our study. Section 4 introduces our estimation methodology. Section 5 reports our results. Section 6 repeats our specification for our "late-sample". Lastly, section 7 concludes.

II. Details of the PPP and PPPLF programs

The PPP was created in response to the COVID-19 virus as part of the Coronavirus Aid, Relief, and Economic Security (CARES) Act to assist small businesses in avoiding bankruptcy during COVID-related activity lockdowns[8]. The nearly $800 billion program was administered by the Treasury Department through the Small Business Administration (SBA). Our study concentrates on SME lending in the PPP, which guaranteed bank loans which firm could use to pay 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 with a maximum of $10 million. Loans were subject to forgiveness by the Treasury under certain conditions, including maintenance of employee headcount or salary levels during the 24-week period after the loan was originated.[9]

PPP loans were primarily underwritten by banks, although "fin-tech" and other non-bank lenders also participated in the program.[10] Banks could charge up to 5% of principal on loans up to $350,000 under the PPP program. The maximum rate fell to 3% on loans between $350,000 and $2 million, and 1% on loans between $2 and $10 million. Banks also received fees from the SBA for administering these loans, which ended up being a non-trivial component of profits earned under PPP lending. Despite the relatively low rates, this combination of administration fees and the fact that the loans were close to risk-free left them attractive to banks. Moreover, PPP

[8]See Hubbard and Strain (2020), Berger and Demirgüç-Kunt (2021), and Lopez and Spiegel (2023) for further details

[9]In the first tranche of disbursement, salary levels were required to be maintained for an 8 week period Lopez and Spiegel (2023).

[10]See Erel and Liebersohn (2022) and Griffin et al. (2023).

loans were assigned a zero weight for capital requirements leaving them attractive from a regulatory point of view as well.

To ease liquidity concerns raised by elevated lending associated with bank participation in the PPP, the Federal Reserve established the PPPLF. This program allowed eligible financial institutions to use PPP loans as collateral at face value in borrowing from the Federal Reserve (e.g. Liu and Volker (2020) and Anbil et al. (2023)). No fees were charged under the program, and credit was provided at an interest rate of 35 basis points. PPPLF loan amounts and maturities were set equal to the terms of the pledged PPP loan. In the event of loan forgiveness, default, or retirement via SBA purchase, PPPLF loan maturity dates were accelerated. In addition to providing funding support to the PPP, the federal banking regulatory agencies allowed banks to exclude any PPP loans used as PPPLF collateral from leverage-based regulatory capital and liquidity requirements (Liu and Volker (2020)).

The required two-page PPP application form yielded little substantive information about firm creditworthiness conducive to the formation of a long-standing banking relationship.[11] On the first page, firms were required to provide information about address, size, intended use of the loan, and identities of owners with greater than 20% equity stakes in the firm. Optional questions provided some demographic details about the applicant. The second page of the application did include informative questions concerning outstanding delinquencies, bankruptcies, and incarceration histories of owners. However, improper responses to these questions immediately barred the applicant from PPP loan approval. In the end, information obtained from the second page of the PPP application form only added information on ownership of additional businesses, prior receipt of COVID-related SBA disaster lending, the firm's franchise status, and if employees were predominantly located in the United States.

III. Data

Our main dataset is half-yearly 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. Our data is biannual, corresponding to ends of quarters 2 and 4. We limit our analysis to these quarters as Call Report coverage is incomplete, particularly for smaller banks, during quarters 1 and 3. We use 2019H2 data to characterize bank conditions going into the

[11]The PPP program form is available at https://home.treasury.gov/system/files/136/PPP-Borrower-Application-Form.pdf.

pandemic and 2020H1 data to examine the extent of SME participation in the PPP and PPPLF programs. This date corresponds to the peak of bank PPP exposure over our sample period.

Our sample is a cross-section of U.S. commercial banks. To be included in the sample, banks must have reported some level of small business or farm lending on their Call Reports in 2019H2. Reporting banks are separated into three categories based on asset size in 2019H2. Our designations follow Call Report conventions, with small banks defined as those with assets below $10 billion, large banks with assets exceeding $100 billion, and medium-sized banks between them. Our base specification sample contains 4,079 banks, of which 3,415 are classified as small banks, 554 as medium-size banks, and 110 as large banks. We also 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 loan volume outstanding, as per Call Report filings, to total assets.[12] $PPPLF$ is defined as the ratio of bank borrowing from the PPPLF program relative to total lending including the borrowing from the PPPLF.[13] To remove the influence of outliers and reporting errors, we winsorize our base specification data set at the 2.5%-97.5% level.[14]

The aggregate evolution of SME and PPP lending from the second half of 2019 to the first half of 2023 is summarized in Table 1. The dates selected begin prior to the pandemic at the end of 2019H2 and continue through the peak of the PPP program in 2020H1. The final dates show two and three years after the peak of the program in 2022H1 and 2023H1 respectively.

[12]Call Report reporting is compulsory for regulated banks, so there are no endogeneity issues in reporting patterns. The Call Report was restructured as of 2020H1 to collect information on PPP loan origination. Banks were instructed to "separately report" PPP and PPPLF exposure, with conventional SME lending reported on Schedule RC-C, Part II of the Call Report.

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

[14]Some individual firm SME lending growth was particularly high at the launch of the PPP program, as some banks with little SME exposure became active PPP participants. Prior to winsorization, some banks SME lending grew over ten times during the half year ending in 2020H1. In the appendix, we also show that our base specification results are robust to truncating our sample instead of winsorizing, as well as not winsorizing or winsorizing at the 0.0%-95.0% levels.

Table 1. Evolution of SME, PPP, and Total Lending Over Time in Hundreds of Billions of Dollars

Sample	Lending	2019H2	2020H1	2022H1	2023H1
FULL	SME	6.41	8.81	6.85	7.18
	PPP	0.00	4.47	0.26	0.05
	TOTAL	6.41	13.28	7.11	7.23
SMALL	SME	1.70	2.21	1.85	1.91
	PPP	0.00	0.76	0.02	0.00
	TOTAL	1.70	2.97	1.87	1.91
MID	SME	1.42	2.08	1.59	1.62
	PPP	0.00	1.11	0.07	0.01
	TOTAL	1.42	3.19	1.66	1.63
LARGE	SME	3.30	4.52	3.41	3.65
	PPP	0.00	2.60	0.17	0.03
	TOTAL	3.30	7.31	3.58	3.68

Note: SME lending refers to small business and farm lending. PPP lending is PPP loan volume outstanding, as per Call Report filings. Total lending is the sum of SME and PPP lending. Four time periods are included. 2019H2 shows lending prior to the pandemic and 2020H1 displays lending at the peak of the PPP program during the start of the pandemic. The final dates, 2022H1 and 2023H1, show lending two and three years after the peak of the program respectively.

Following the introduction of the PPP program in the first half of 2020, total lending experiences a pronounced increase due to the high number of PPP loans. However, conventional SME lending also increases markedly, with the result that total lending to SME firms more than doubled over the six month period.

After the peak in 2020H1, PPP exposure falls precipitously, as loans are forgiven or paid off. By the end of the sample in 2023H1, outstanding PPP loan exposure is almost reduced to zero. SME lending falls as well, but at a much more modest pace.

Our dependent variables are measures of growth in SME lending at the bank level. $\%\Delta SME$ is a measure of average annualized growth in small business and farm lending between 2019H2 and 2023H1. Our dependent variables also are winsorized at the 2.5%-97.5% level to reduce the influence of reporting errors and outliers.

As our sample is a cross-section, we introduce explicit variables to condition on differences in individual bank characteristics. The time period of our conditioning variables corresponds to the end of 2019H2, i.e. just prior to the COVID period and the launch of the PPP program. 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.

Our conditioning variables include $LIQUID$, which measures bank cash and security holdings as a share of total assets, as a measure of bank liquidity. We include $DEPOSITS$, which measures core deposits relative to total assets to capture a bank's reliance on deposit funding. We also include $TIER1CAP$, a measure of tier one capital relative to total risk-weighted assets, and $COMMIT$ as a measure of outstanding loan commitments, which has been shown to play a major role in the pricing and availability of credit lines during the COVID crisis [e.g. Greenwald et al. (2020)]. We include $SME19H2$, a measure of small business and farm lending normalized by total assets in 2019H2 to account for existing disparities between banks in small business lending prior to the pandemic. Finally, we include $PROB$ as an aggregate measure of past-due and non-accrual "problem" loans relative to total assets all at the bank level.

Summary statistics for our dependent variables and explanatory variables of interest under our base specification sample are shown in Table 2.[15] Our sample exhibits a large amount of variability across banks, with the standard deviation of average annual growth in SME lending almost double the sample mean value for that variable. It can also be seen that mean values for all bank size groups for our dependent variable, $\%DeltaSME$, are consistently above median values, suggesting that even after winsorizing our sample is skewed to the right by some banks with very high SME lending growth. Growth in SME lending is largest on average for our large bank sub-sample. Relative SME lending exposure going into the pandemic ($SME19H2$) was highest among small banks and lowest among large banks, with average small bank exposure almost triple that of large banks. The high exposure going into the pandemic likely explains some of the lower growth on average for small banks over our sample period, but some large banks also capitalized on existing web presences to attract firms under the PPP program due to their ease of application and ability to distribute funds quickly [Lopez and Spiegel (2023)].

[15]Summary statistics for other conditioning variables are shown in Online Appendix Table O.A1.

TABLE 2. Summary Statistics by Bank Size

SAMPLE		N	Median	Mean	SD	Min	Max
FULL	$\%\Delta SME$	4,079	0.047	0.078	0.154	-0.144	0.755
	$\%\Delta SME22$	4,079	0.023	0.037	0.159	-0.313	0.669
	PPP	4,079	0.041	0.051	0.044	0.000	0.188
	$PPPLF$	4,079	0.000	0.025	0.077	0.000	0.337
	$SME19H2$	4,079	0.166	0.179	0.101	0.011	0.437
SMALL	$\%\Delta SME$	3,415	0.045	0.078	0.158	-0.144	0.755
	$\%\Delta SME22$	3,415	0.029	0.044	0.158	-0.313	0.669
	PPP	3,415	0.037	0.049	0.045	0.000	0.188
	$PPPLF$	3,415	0.000	0.022	0.072	0.000	0.337
	$SME19H2$	3,415	0.184	0.194	0.099	0.011	0.437
MID	$\%\Delta SME$	554	0.060	0.077	0.127	-0.144	0.755
	$\%\Delta SME22$	554	-0.008	0.000	0.145	-0.313	0.669
	PPP	554	0.058	0.062	0.040	0.000	0.188
	$PPPLF$	554	0.000	0.040	0.098	0.000	0.337
	$SME19H2$	554	0.102	0.107	0.063	0.011	0.437
LARGE	$\%\Delta SME$	110	0.063	0.095	0.181	-0.144	0.755
	$\%\Delta SME22$	110	-0.034	0.004	0.219	-0.313	0.669
	PPP	110	0.042	0.039	0.031	0.000	0.188
	$PPPLF$	110	0.000	0.036	0.098	0.000	0.337
	$SME19H2$	110	0.035	0.051	0.044	0.011	0.235

Note: Winsorized at 2.5%-97.5% levels. $\%\Delta SME$ is average annualized growth in small business and farm lending between 2019H2 and 2023H1; $\%\Delta SME22$ is average annualized growth in small business and farm lending from 2022H1 through 2023H1; PPP is the ratio of PPP participation to total assets in 2020H1; and $PPPLF$ is the ratio of bank borrowing from the PPPLF program to total lending (including PPP lending) in 2020H1. $SME19H2$ is small business and farm lending normalized by total assets in 2019H2.

IV. ESTIMATION

IV.1. **Model specification.** We are interested in identifying the impact of participation in the PPP and PPPLF programs on longer-term SME lending. We use participation at the peak of the programs, 2020H1, as our measure of program participation. Our sample is the full cross section of U.S. commercial banks included in the Call Report, and we examine average annual growth over our entire sample period in SME lending as our base specification dependent variable.[16]

[16]Due to data availability, our full sample under our base specification is 4,079 banks.

As we are interested in identifying a causal relationship, we use instrumental variables estimation. However, as the measures of participation in the PPP and PPPLF are highly correlated, we examine the impact of participation in each program separately.[17]

Our dependent variable is $\%\Delta SME_i$, the average annual growth in a bank's small business and farm lending from the end of 2019H2 through end 2023H1. To identify a causal relationship between program participation we run a two-stage least squares specification, with the second stage of our base specification for the impact of PPP participation satisfying:

$$\%\Delta SME_i = c + \beta_1 PPP_i + \beta X_i + \beta_2 SMALL_i + \beta_3 MED_i + \epsilon_i \tag{1}$$

where β_1 represents our coefficient estimate of interest, 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.

To deal with potential correlation in standard errors across bank groups by size, we cluster our standard errors by bank size. Large banks face different funding and lending opportunities than small or medium-sized banks, who also likely differ from each other. For example, large banks enjoy superior ability to issue their own commercial paper, which could leave them relatively less sensitive to the liquidity advantages under the PPPLF program. As shown in Table 2, large banks are also less exposed to SME lending as a share of total assets than their small and medium-sized counterparts.

To allow for the outsized importance of large bank lending growth in determining the aggregate response of SME lending to the PPP and PPPLF programs, we then repeat our base specification using weighted least squares, with observations weighted by bank total assets. Finally, to allow for disparities in sensitivity to program participation by bank size, we also repeat our base specification for the three bank size sub-groups separately, with our base specification for these sub-samples with White heteroscedasticity-robust standard error estimation.

Our specification for the impact of PPPLF participation on small business and farm lending growth satisfies

[17] The correlation coefficient between our measures of PPP and PPPLF program participation in our base sample is 0.41. We ran the base specification with both PPP and PPPLF participation variables included, instrumenting for both. However the high correlation between the two measures of program participation resulted in the PPP variable entering negatively and the $PPPLF$ variable entering positively. Results for this specification are available on request.

$$\%\Delta SME_i = c + \beta_1 PPPLF_i + \beta X_i + \beta_2 SMALL_i + \beta_3 MED_i + \epsilon_i \tag{2}$$

where β_1 is again our coefficient of interest, X_i denotes the set of conditioning variables discussed above, and ϵ_i is the residual. We again cluster standard errors by bank size, and then repeat our PPPLF specification with weighted least squares and with our sample separated into small, medium, and large bank sub-samples.

IV.2. **Identification.** Bank participation in the PPP and PPPLF programs is likely endogenous to the impact of the COVID-19 pandemic on bank fundamentals. For any SME loan, lending decisions likely incorporated bank plans concerning submission of that loan to the PPP and use of the extended loan as collateral under the PPPLF. These considerations could also influence SME lending after the termination of the programs, due to the relationships developed between borrowers and lenders while the program was in place.

To respond to the likely endogeneity of PPP and PPPLF participation, we use instrumental variables estimation. We follow Anbil et al. (2023) and Lopez and Spiegel (2023) and consider two types of instruments for both PPP and PPPLF program participation. First, we consider two indicators of the intensity of bank interaction with the Small Business Administration (SBA), the agency responsible for administering PPP lending, in 2019. Greater connections to the SBA going into the crisis likely facilitated bank participation in both programs. Lenders that were already certified as SBA 7(a) banks prior to the launch of the PPP were automatically eligible for the PPP program. Lenders who were not previously certified were required to file SBA Lender Agreement form 3506 to become eligible for the PPP [Barraza et al. (2020)]. In turn, by encouraging greater PPP participation, previous experience with the SBA likely also left banks with more PPP loans on their balance sheets, and hence greater incentive for PPPLF participation as well.

Our identification strategy requires that prior interactions with the SBA only affected growth in lending over our sample period through its influence on the degree of participation in the PPP and PPPLF. Satisfaction of this condition is supported by studies to date that have shown that PPP lending was greater in areas that were more served by the SBA in 2019 (Liu and Volker (2020)), and were essentially uncorrelated with prevailing economic conditions (Granja et al. (2022)).

Our first instrument SBA_i is specified as the ratio of SBA lending by bank i, $SBALEND_i$, to total bank i small business and farm lending, SME_i, measured at year-end 2019:

$$SBA_i = \frac{SBALEND_i}{SME_i}. \tag{3}$$

Our second instrument for pre-pandemic interaction with the SBA is that used in Lopez and Spiegel (2023), $INDMIX_i$, which estimates the similarity of a bank's lending portfolio to that of the SBA at 2019H2. SME lending in industries which were also prevalent in SBA portfolios are likely to have encouraged prior familiarity with the SBA, and hence an initial advantage in garnering PPP funds. Using six-digit NAICS codes, the imilarity of a bank i lending portfolio and that of the SBA satisfies

$$INDMIX_i = \sum_j \left(\frac{SBA_j}{SBA} \cdot \frac{BUSF_{i,j}}{BUSF_i} \right), \tag{4}$$

where SBA_j represents SBA lending to industry j, SBA represents total SBA lending, $BUSF_{i,j}$ 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 at 2019H2. It is easy to verify that $INDMIX_i$ is increasing in the similarity of the industry mixes of bank i and that of the SBA.

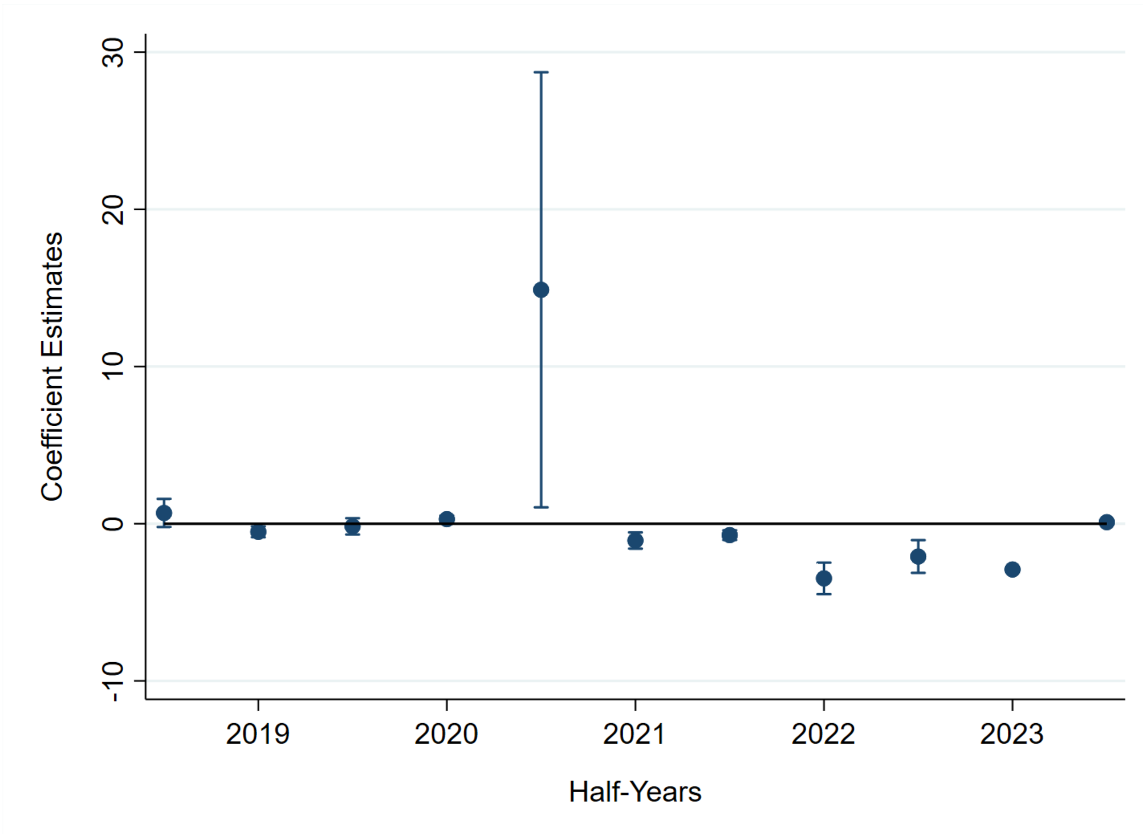
As our third and fourth instruments, we use indicators of familiarity with the Federal Reserve discount window, which administered the PPPLF. Again, both values calculated at 2019H2, prior to the onset of the pandemic and the PPP and PPPLF programs. As discussed by Anbil et al. (2023), the practice of pledging standard loan collateral and obtaining discount window loans requires that they are prepared for required interaction 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 they are required to submit monthly updates on any changes in their asset values. These requirements are very close to those needed to qualify for pledging PPP loans to the PPPLF.[18]

We also expect that these instrumental variables will influence both PPP and PPPLF participation. A bank's decision to issue a PPP loan is likely to be dependent on its perceived probability that the loan can be converted into cash by submitting it as collateral to the PPPLF. We use 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 bank's total collateral pledged to the discount window program ($COLLATERAL_i$).

[18]This data is proprietary to the Federal Reserve and is not publicly available.

IV.3. **Half-year univariate results.** We first conduct a preliminary exercise to demonstrate that the impact of our instrumented variable of interest directly reflects the launch of the PPP program (and the the instrumented PPP variable has the expected contemporaneous impact on SME lending), rather than spurious correlations with existing bank-specific characteristics. We run a univariate regression of annualized SME lending growth for each half year from 2018H1, long before the onset of the pandemic, through 2023H1 on our instrumented PPP_i variable.[19]

FIGURE 3. Half-year Univariate Regressions



Note: Each point represents the coefficient estimate resulting from a univariate regression of average 6-month annualized SME lending growth ending on that date on our instrumented PPP variable for PPP participation in 2020H1. Regressions are run for each half-year from 2018H1 to 2023H1. Standard errors are clustered by bank size. Bars represent 95% confidence intervals.

Our results are shown in Figure 3. Reassuringly, PPP participation in 2020H1 has no effect on SME lending growth prior to the pandemic. Because of our large

[19]The regression results for these univariate half-year regressions re reported in online appendix tables OA.10 and OA.11. Standard errors are clustered by bank size, as in our base specification.

sample, while our coefficient point estimates are all close to zero, some are statistically significant. Still, we obtain both positive and negative values, so that there is no apparent spurious net association between our variable of interest and SME lending activity prior to the onset of the pandemic.[20]

We observe a very large contemporaneous impact of PPP participation in the half-year ending in 2020H1 on lending in that period, as would be expected. Our point estimate suggests that a one standard deviation increase in PPP participation was associated with an 84 percentage point increase in annualized SME lending growth for that half-year.

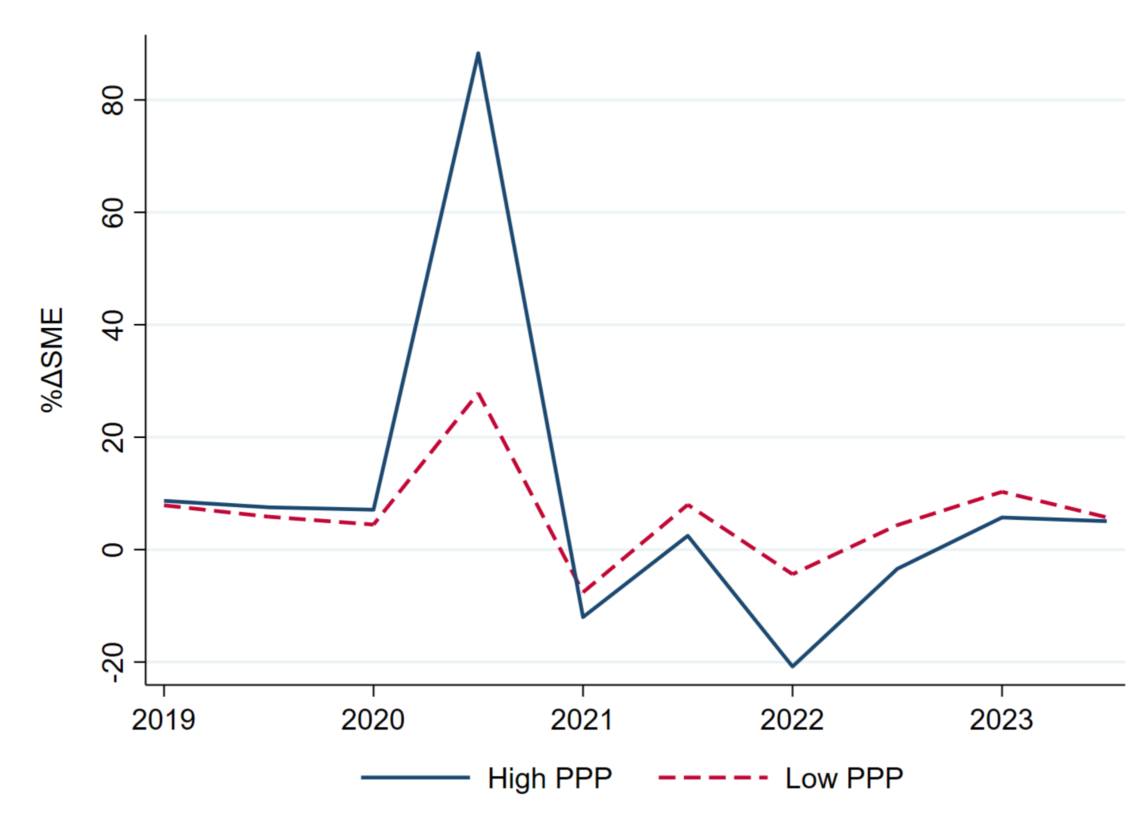
Subsequent to that point, we observe modest declines in SME lending associated with participation in the PPP program at the height of the pandemic. While these are small, some are statistically significant. As we discuss below, these negative values likely reflect bank efforts to correct out-sized increases in SME lending growth in 2020H1 attributable to PPP program participation. However, these declines are far smaller than the large spike in 2020. The net result is therefore a persistent increase in SME lending over the period as a whole, consistent with our full specification results below.

IV.4. **High vs. Low PPP Participation and SME Lending.** As an additional first pass at the data, we split the sample into two based on the sample median intensity of PPP participation at the height of the program at the end of 2020H1, as measured by our PPP variable. Figure 4 plots annualized half-yearly growth rates for banks with above and below-average PPP participation in our base sample. It can be seen that average growth in SME lending in the half year ending in 2020H1 was far higher for the sub-sample of banks that had high PPP participation than it was for those banks that had below median participation in the PPP program, although SME lending for those banks grew at a notable pace as well. Subsequent to that date, the set of banks with high PPP participation had somewhat lower growth in SME lending than the group with low participation. Banks that had participated in the high PPP-group spike in SME lending in 2020H1 likely found themselves with SME lending shares above their desired levels, and moved to rebalance their portfolios in line with their long-term preferences and business models. However, by the end of our sample in 2023H1, growth in SME lending among the two groups had essentially converged.

[20]Full results for these regressions can be found in online appendix Table OA.7.

On average, the disparities in SME lending among the high and low PPP groups subsequent to 2020H1 were sufficiently smaller than the spike during the pandemic that cumulative growth in SME lending over the period as a whole was greater for high-PPP banks. In terms of our metrics, $\%\Delta SME$ is equal to 88% for the high PPP group and 28% for the low PPP group, implying that PPP participation was associated with a persistent increase in SME lending. In the following section, we apply our IV methodology to establish a causal relationship from PPP and PPPLF lending to persistent increases in SME lending.

Figure 4. High vs. Low PPP Participation in SME Lending



Note: Annualized percentage changes in half-year SME lending growth rates for high and low PPP participation banks defined as above and below sample median in 2020H1.

V. PPP participation and lending growth

Our full-sample base IV specification results for PPP participation are shown in Table 5, Column 1, with standard errors clustered by size. Our variable of interest enters positively and significantly at 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 on average with a 3.8 percentage point increase in average annual SME lending growth.

We also evaluate the strength of our instruments. Our Cragg-Donald Wald F statistic is 142.52, which passes the Stock-Yogo weak identification test at a 5% confidence level. Our base results also obtain an Anderson LM statistic of 501.57, which rejects under-identification at a 1% confidence level. We also ran the Montiel-Pflueger weak instrument robust tests and obtain a CLR statistic of 24.45 and an AR statistic of 28.68, both of which reject weak instruments at a 1% confidence level.

For the conditioning variables, we obtain positive and significant coefficient estimates for $LIQUID$, $TIER1CAP$, and $PROB$ at a 1% confidence level, indicating that banks with more liquid balance sheets, higher capital ratios, and somewhat surprisingly, greater shares of problem loans exhibited higher SME lending growth. We obtain significantly negative coefficients at the 1% confidence level for $COMMIT$ and $SME19H2$ at a 5% confidence level, indicating less SME lending growth on average for banks with greater outstanding loan commitments, greater existing exposure to SME lending. $DEPOSITS$ enters insignificantly.[21]

Lastly, our indicator variables for the small bank group enters positively, that for medium-sized banks enters negatively and our constant term enters positively, again all at 1% confidence levels. These results imply higher SME lending growth after conditioning for other bank characteristics is highest on average among small banks, followed by large banks, and then medium-sized banks.

Column 2 reports our results with observations weighted by total assets. While some of the coefficient estimates have changed markedly, the qualitative results are similar, indicating that our conclusions are generally robust to weighting our observations by bank size.

First, our variable of interest continues to enters positively and significantly at a 1% confidence level. However, our point estimate has grown markedly, more than doubling relative to its magnitude in our unweighted base specification. Combined with the summary statistics in Table 2, our point estimate for our weighted least squares specification implies that a one standard deviation increase in PPP is associated with

[21]We also separated the base specification sample according to above and below median values of the covariates, including high and low initial deposit funding, tier1 capital, initial SME lending shares, and problem loans. Our results are qualitatively robust across these sub-samples, as our PPP variable of interest continues to enter positively and with statistical significance throughout. These results can be found in online appendix tables O.A.5 and O.A.6.

Table 3. PPP and Small Business and Farm Lending

	Full	WLS	Small	Medium	Large
PPP	0.864***	2.227***	0.795***	1.445**	2.341
	(0.0859)	(0.0277)	(0.195)	(0.493)	(3.487)
LIQUID	0.131***	1.679***	0.127**	-0.0311	1.264
	(0.0188)	(0.113)	(0.0478)	(0.132)	(0.866)
COMMIT	-0.246**	-1.585***	-0.311	-0.110	-0.714
	(0.0824)	(0.148)	(0.171)	(0.261)	(0.507)
DEPOSITS	-0.0180	-0.142***	-0.0387	0.0200	-0.0627
	(0.0249)	(0.0115)	(0.0578)	(0.112)	(0.400)
TIER1CAP	0.0679***	-0.505***	0.0637	-0.0314	-0.247
	(0.0136)	(0.0480)	(0.0595)	(0.195)	(0.759)
SME19H2	-0.379***	-0.642***	-0.379***	-0.431**	-1.055
	(0.00357)	(0.0239)	(0.0295)	(0.139)	(0.994)
PROB	0.0864***	-0.223***	0.0661	0.0486	-0.492
	(0.0252)	(0.0114)	(0.167)	(0.559)	(1.484)
SMALLBANK	0.00950***	-0.0780***			
	(0.00121)	(0.00660)			
MIDBANK	-0.0223***	-0.0645***			
	(0.00133)	(0.00266)			
CONSTANT	0.0956**	0.259***	0.129*	0.0280	0.129
	(0.0304)	(0.00288)	(0.0534)	(0.102)	(0.315)
N	4079	4079	3415	554	110

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: IV estimation with dependent variable $\%\Delta SME$, average annualized growth in small business and farm lending between 2019H2 and 2023H1. PPP is the the ratio of a bank's PPP participation to total assets in 2020H1; $LIQUID$ is a bank's total liquidity in 2019H2; $COMMIT$ is unused commitments in 2019H2; $DEPOSITS$ is a bank's total deposits in 2019H2; $TIER1CAP$ represents a bank's tier 1 capital ratio; $SME19H2$ is a measure of small business and farm lending normalized by total assets in 2019H2; $PROB$ is a bank's aggregate measure of past-due and non-accrual loans relative to total assets in 2019H2; and $SMALLBANK$ and $MIDBANK$ are indicator variables for small and medium-sized banks, respectively. See text for instruments used for PPP. Column 2 estimated by weighted least squares, with observations weighted by total assets. Columns 3, 4, and 5 represent the sample of small, medium, and large banks respectively. Standard errors in parentheses are clustered by bank size.

a larger 9.8% increase in average annual small business and farm lending growth over our sample period.

Our conditioning variables enter significantly with the same signs as they had in our unweighted specification, with two exceptions: $TIER1CAP$ and $PROB$ now enters negatively and statistically significantly. The change in sign for $PROB$ would be expected. One would think that as SME lending outside of the PPP program was relatively risky, particularly during the pandemic period. This suggests that banks with a greater share of initial problem loans would be relatively discouraged from growth in SME lending. The impact of tier-1 capital ratios on bank SME lending is ambiguous, as low tier-1 capital ratios may leave banks more constrained in their SME lending capacity, but may also reflect a bank's willingness to pursue a more aggressive lending strategy, which may leave the bank open to even higher SME lending.

Columns 3, 4, and 5 report results for our bank size sub-samples, estimated with robust standard errors. We obtain positive and statistically significant coefficient point estimates for our PPP variable of interest for small and medium-sized banks, but PPP enters positively but insignificantly for our large bank sub-sample. We therefore conclude that our full sample results for a significant positive impact of PPP participation are largely driven by the small and mid-sized banks in our sample. It is also notable that with our samples split by bank size groups, our conditioning variables lose much of their significance. This may indicate that the results for conditioning variables in our full sample may be driven by systematic discrepancies by bank size.

In the appendix, we subject our base specification to a number of changes in specification, including dropping the conditioning variables, using total capital ratio instead of our tier-1 risk adjusted measure, conditioning for lagged SME lending growth from 2018H1 through 2019H2, measuring long-term SME growth for our sample based on initial and final values in 2019H2 and 2023H1, and estimating PPP participation as a qualitative variable. In all cases, our coefficient on PPP participation remains positive at statistically significant levels.

We also examine changes in our sample (appendix Table A.2), including truncating SME growth outliers at the 2.5-97.5% level instead of winsorizing, winsorizing at 1-99% and 5-95, and separating the sample into DFAST samples. This latter separation identifies those banks that are subject to regulatory stress testing. This differs modestly from our large bank sample.[22] The estimates coefficient on the PPP variable

[22]The set of banks included in the DFAST sub-sample are listed in the online appendix, Table O.A.12.

remains positive for all specification, with the notable exception of the DFAST subsample, for which the PPP variable enters insignificantly. This distinction is notable, as it suggests that the same specification based on a cross-section of Y-14 DFAST banks would fail to identify a significant persistent role for PPP participation in SME lending growth.

Finally, Table A.3 examines robustness to changes in estimation methods, including estimation under least squares, regular standard errors, White's robust standard errors, clustering by geographic region instead of bank size, TOBIT estimation of the first-stage (as our PPP participation is bounded between 0 and 1), and weighted least squares with weighting by bank shares of SME lending. Our qualitative results remain the same, as PPP continues to enter positively and at statistically significant levels in all specifications.

V.1. **PPPLF participation and lending growth.** Our base specification results for the persistent impact of PPPLF participation are shown in Table 4. Column 1 displays our base IV specification with $PPPLF$ participation as the variable of interest with standard errors clustered by size. As was the case for PPP participation, this variable also enters positively and significantly at 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 4.9 percentage point increase in average annual small business and farm lending growth over our sample period.

Our instrumented $PPPLF$ variable also passes our weak instrument tests. Our Cragg-Donald Wald F statistic is 61.08, which passes the Stock-Yogo weak identification test at a 5% confidence level. Our base results also obtain an Anderson LM statistic of 231.22, which rejects under-identification at a 1% confidence level. We also ran the Montiel-Pflueger weak instrument robust tests and obtain a CLR statistic of 23.54 and an AR statistic of 28.68, both of which reject weak instruments at a 1% confidence level.

For the conditioning variables, we again obtain positive and significant coefficient estimates for $LIQUID$ and $TIER1CAP$, supporting the inference that banks with more liquid balance sheets and higher capital ratios exhibited higher SME lending growth. We also again obtain significantly negative coefficients at the 1% confidence level for $SME19H2$ indicating again less SME lending growth on average for banks with greater greater existing exposure to SME lending.

Table 4. PPPLF and Small Business and Farm Lending

	Full	WLS	Small	Medium	Large
PPPLF	0.632***	-0.0464	0.585***	0.852**	-0.230
	(0.0576)	(0.136)	(0.141)	(0.306)	(1.506)
LIQUID	0.171***	1.490***	0.174***	-0.0597	0.826
	(0.0221)	(0.0975)	(0.0461)	(0.138)	(0.654)
COMMIT	0.0822	-1.548***	0.0342	0.286	-0.593
	(0.0872)	(0.265)	(0.114)	(0.197)	(0.479)
DEPOSITS	0.0641	-0.0359	0.0256	0.173	-0.0473
	(0.0381)	(0.0617)	(0.0613)	(0.132)	(0.565)
TIER1CAP	0.0836***	-0.845***	0.0691	0.128	-0.667
	(0.0236)	(0.145)	(0.0620)	(0.238)	(0.790)
SME19H2	-0.330***	-0.285*	-0.346***	-0.100	-0.533
	(0.0213)	(0.120)	(0.0321)	(0.113)	(0.755)
PROB	-0.143***	-1.001***	-0.119	-0.667	-0.811
	(0.0125)	(0.101)	(0.165)	(0.602)	(1.429)
SMALLBANK	0.0295***	-0.0334***			
	(0.000356)	(0.00711)			
MIDBANK	-0.00449***	-0.00252			
	(0.00110)	(0.00309)			
CONSTANT	0.0138	0.274**	0.0832	-0.111	0.265
	(0.0414)	(0.0951)	(0.0576)	(0.125)	(0.601)
N	4079	4079	3415	554	110

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: IV estimation with dependent variable $\%\Delta SME$, average annualized growth in small business and farm lending between 2019H2 and 2023H1. $PPPLF$ is the the ratio of a bank's borrowing from the PPPLF program to total assets in 2020H1; $LIQUID$ is a bank's total liquidity in 2019H2; $COMMIT$ is unused commitments in 2019H2; $DEPOSITS$ is a bank's total deposits in 2019H2; $TIER1CAP$ represents a bank's tier 1 capital ratio; $SME19H2$ is a measure of small business and farm lending normalized by total assets in 2019H2; $PROB$ is a bank's aggregate measure of past-due and non-accrual loans relative to total assets in 2019H2; and $SMALLBANK$ and $MIDBANK$ are indicator variables for small and medium-sized banks, respectively. See text for instruments used for PPP. Column 2 estimated by weighted least squares, with observations weighted by total assets. Columns 3, 4, and 5 represent the sample of small, medium, and large banks respectively. Standard errors in parentheses are clustered by bank size.

However, we also obtain a number of results for the conditioning variables which contradict our instrumented PPP specification. Most notably, we obtain switches in sign for $PROB$, which now enters significantly with a more intuitive negative sign at a 1% confidence level, while $DEPOSITS$ enters marginally positively at a 10% confidence level. The $COMMIT$ and $DEPOSITS$ variables are insignificant. Overall, the discrepancies obtained for a number of conditioning variables highlights the importance of our demonstration that our base results are also robust to the exclusion of them in appendix Table A1.[23]

The remainder of the table repeats our specifications with variables weighted by total assets (Column 2), and the base specification for sub-samples of small, medium and large banks (Columns 3, 4, and 5 respectively). $PPPLF$ is statistically insignificant with a negative point estimate in our weighted specification. This discrepancy is likely driven by the weaker dependence of large banks on the PPPLF as a tool for liquidity enhancement while participating in the PPP program. We see a similar pattern among our sub-sample specifications, as the $PPPLF$ sub-sample continues to enter significantly positively for our small and medium-sized banks sub-samples, with coefficient point estimates close to that which we obtained for our full sample specification, while the $PPPLF$ variable enters insignificantly with a negative point estimate for our large bank sub-sample. Again, this likely reflects the greater importance of the PPPLF program for the liquidity positions of small and medium-sized banks as SME lending was not as large a component of large bank balance sheets.[24]

VI. Late-sample effects of PPP and PPPLF lending

As shown in Figure 4, the rapid rise in SME lending in 2020 was partially offset by a decline in SME exposure over the later portion of our data set that was more

[23] We again separated the base specification sample according to above and below median values of the covariates for the base specification with the $PPPLF$ variable as our variable of interest in the online appendix (Tables O.A. 7 and O.A.8). Our results are again qualitatively robust across these sub-samples, as our $PPPLF$ variable of interest continues to enter positively and with statistical significance throughout.

[24] We also repeat the robustness exercises we ran for the effects of PPP participation for PPPLF participation, allowing for the same changes in specification, sample, and estimation methods. Our results are qualitatively the same, with the exception that while the $PPPLF$ coefficient estimate remains positive, it now enters statistically insignificant. These robustness tests are available in the online appendix, Tables OA.1 through OA.3 respectively.

pronounced among the high PPP participants than it was among the low PPP participants. This period was also associated with a sharp decline in PPP exposure, which was close to zero by the end of our sample in 2023H1.

In this section, we examine whether the decline in SME lending subsequent to the peak of the PPP program was causally related to bank participation in the PPP and PPPLF programs.

We restrict our analysis to the last year of our sample, i.e. the period between 2022H1 and 2023H1. By this time, PPP loans outstanding had fallen close to zero, as most PPP debt had been either forgiven or repaid.[25]

Our dependent variable for this period is $\%\Delta SME22$, which measures average annualized growth in SME lending between 2022H1 and 2023H1. Our variables of interest are the same, PPP and $PPPLF$, measured as of the peak of both programs in 2020H1 and instrumented as before. If the decline in SME lending that we observe in aggregate after PPP loan exposure had fallen to zero was systematically related to earlier participation in the PPP and PPPLF programs, we would expect to obtain a negative coefficient estimate on these variables. We also include the same conditioning variables as our base specification, with values update to 2022H1, i.e. immediately prior to our later sample period.

Our results for growth over the latter portion of our sample and PPP participation are shown in Table 5. PPP enters significantly with a negative coefficient estimate for all specifications and samples, with the exception of the large bank sub-sample, for which PPP enters insignificantly, as it did for our full time series. Our point estimate indicates that a 1% increase in PPP was associated with an annualized decrease in growth of 3.7 percentage point over the last year of our sample period.[26]

In contrast to the results we get for PPP participation, our conditioning variable for SME exposure going into the latter portion of our sample, $SME22H1$, tends to enter insignificantly, with the exception of the WLS specification and the medium-sized bank sub-sample, which enter significantly positive. Our full sample results suggest that SME exposure after the bulk of PPP exposure had been retired in 2022H1 was

[25]For our sample of banks, total PPP lending had declined to only 26 billion dollars by 2022H1.

[26]We demonstrate in the online appendix that our results are robust to conditioning for growth in SME lending over the earlier portion of our sample period, i.e. from 2019H2 through 2022H1, both with and without conditioning for the initial level of SME lending in 2022H1. We also demonstrate that our qualitative results for PPP are robust to dropping $SME22H1$, and that our results for $SME22H1$ are robust to dropping PPP and re-estimating the equation under OLS. These robustness checks can be found in online appendix Table OA.9.

Table 5. PPP and Small Business and Farm Lending 2022H1 to 2023H1

	Full	WLS	Small	Medium	Large
PPP	-0.837***	-1.454***	-0.870***	-1.310*	-3.213
	(0.0165)	(0.394)	(0.182)	(0.641)	(4.173)
LIQUID22	-0.00468	0.491***	-0.0118	0.0448	0.330
	(0.00560)	(0.0355)	(0.0355)	(0.114)	(0.546)
COMMIT22	0.373***	-0.320***	0.439**	0.528*	-0.423
	(0.0492)	(0.0772)	(0.151)	(0.234)	(0.315)
DEPOSITS22	0.0216	-0.521***	-0.0127	0.263	-0.234
	(0.0629)	(0.0917)	(0.0676)	(0.135)	(0.706)
TIER1CAP22	-0.0585***	-0.586***	-0.0547	-0.0590	-1.112
	(0.00154)	(0.110)	(0.0341)	(0.116)	(0.729)
SME22H1	0.0334	0.772***	-0.00399	0.583***	1.579
	(0.0382)	(0.00212)	(0.0283)	(0.133)	(1.356)
PROB22	-0.465***	0.509	-0.408	-0.630	-0.390
	(0.0514)	(0.304)	(0.256)	(0.553)	(1.147)
SMALLBANK	0.0627***	-0.0530***			
	(0.00593)	(0.0112)			
MIDBANK	0.0218***	-0.00873			
	(0.00263)	(0.0129)			
CONSTANT	-0.00193	0.512***	0.0978	-0.227*	0.412
	(0.0589)	(0.106)	(0.0602)	(0.108)	(0.502)
N	4079	4079	3415	554	110

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: IV estimation with dependent variable $\%\Delta SME22$, average annualized growth in small business and farm lending between 2022H1 and 2023H1. PPP is the the ratio of a bank's PPP participation to total assets in 2020H1; $LIQUID22$ is a bank's total liquidity in 2022H1; $COMMIT22$ is unused commitments in 2022H1; $DEPOSITS22$ is a bank's total deposits in 2022H1; $TIER1CAP22$ represents a bank's tier 1 capital ratio; $SME22H1$ is a measure of small business and farm lending normalized by total assets in 2022H1; $PROB22$ is a bank's aggregate measure of past-due and non-accrual loans relative to total assets in 2022H1; and $SMALLBANK$ and $MIDBANK$ are indicator variables for small and medium-sized banks, respectively. All columns are instrumental variable regressions. Columns 2 includes weighted least squares specifications. Columns 3, 4, and 5 represent the sample of small, medium, and large banks respectively. Standard errors in parentheses are clustered by bank size.

not a deterrent to further SME lending growth for the bulk of the banks in our sample. Indeed, medium-sized banks that had larger exposure going into the last year of our sample had higher growth over that period, and initial exposure enters insignificantly for other banks in our sample.[27]

We next repeat the exercise for the impact of PPPLF participation over the latter period of our sample, using our instrumented $PPPLF$ variable. Again, our base specification has dependent variable $\%\Delta SME22$, average annualized growth in SME lending between 2022H1 and 2023H1, while all of our conditioning variables measure bank characteristics going into this latter sample portion at 2022H1.

Our $PPPLF$ variable enters significantly negatively at a 1% confidence level for all specifications except our large bank sub-sample. This pattern qualitatively matches the results we obtained above for our PPP variable. Our point estimate for the full sample specification indicates that a one standard deviation increase in $PPPLF$ was associated in a 5.2 percentage point decrease in average annualized SME lending growth between 2022H1 and 2023H1. It therefore also appears to be the case that with the exception of the large bank sub-sample, banks with higher participation in the PPPLF program were also drawing down their SME exposure over this latter portion of our sample.

These results for the $PPPLF$ variable contrast again with those that we find for the $SME22H1$ variable measuring overall bank exposure to SMEs going into the last year of our sample. We obtain an insignificant coefficient estimate on this variable for all but the medium-sized banks, which again enters significantly positive, suggesting that medium-sized banks with higher SME exposures actually had higher SME growth on average for the final year of our sample.[28]

We interpret our late sample negative coefficient estimates on the PPP and $PPPLF$ variables as indicating that banks found themselves with extraordinarily high levels

[27]We show in the online appendix that the significantly negative coefficient estimates on PPP are robust to excluding the $SME22H1$ variable. We also conditioned for average annualized SME lending growth over the earlier portion of the sample, i.e. from 2019H2 through 2022H1, both with and without the initial SME lending growth conditioning variable, $SME22H1$. This variable entered positively in both cases at a 10% confidence level, but did not qualitatively change our point estimate for our PPP variable of interest.

[28]We also show that that the significantly negative coefficient estimates on $PPPLF$ over this period are robust to excluding the $SME22H1$ variable or conditioning for average annualized SME lending growth over the earlier portion of the sample, both with and without the initial SME lending growth conditioning variable.

Table 6. PPPLF and Small Business and Farm Lending 2022H1 to 2023H1

	Full	WLS	Small	Medium	Large
PPPLF	-0.670***	-1.288***	-0.685***	-0.724	-2.756
	(0.0355)	(0.0281)	(0.163)	(0.398)	(2.178)
LIQUID22	-0.0371***	0.520***	-0.0509	0.0221	0.117
	(0.00975)	(0.0385)	(0.0353)	(0.127)	(0.561)
COMMIT22	0.160	-0.520***	0.134	0.350*	-0.664
	(0.0890)	(0.119)	(0.115)	(0.171)	(0.405)
DEPOSITS22	-0.0794	-0.918***	-0.105	0.105	-1.292
	(0.0614)	(0.154)	(0.0705)	(0.130)	(0.752)
TIER1CAP22	-0.0655***	-0.646***	-0.0581	-0.110	-1.196
	(0.00518)	(0.0901)	(0.0348)	(0.111)	(0.779)
SME22H1	-0.00986	0.182	-0.0370	0.341**	-0.264
	(0.0294)	(0.175)	(0.0303)	(0.108)	(1.001)
PROB22	-0.180***	0.971***	-0.179	-0.149	2.283
	(0.0300)	(0.247)	(0.248)	(0.662)	(2.652)
SMALLBANK	0.0444***	-0.0255			
	(0.00176)	(0.0205)			
MIDBANK	0.00403***	-0.0153*			
	(0.000548)	(0.00732)			
CONSTANT	0.0945	0.893***	0.168**	-0.104	1.376
	(0.0615)	(0.160)	(0.0638)	(0.115)	(0.763)
N	4079	4079	3415	554	110

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: IV estimation with dependent variable $\%\Delta SME22$, average annualized growth in small business and farm lending between 2022H1 and 2023H1. $PPPLF$ is the ratio of a bank's borrowing from the PPPLF program to total lending including the borrowing from the PPPLF in 2020H1; $LIQUID22$ is a bank's total liquidity in 2022H1; $COMMIT22$ is unused commitments in 2022H1; $DEPOSITS22$ is a bank's total deposits in 2022H1; $TIER1CAP22$ represents a bank's tier 1 capital ratio; $SME22H1$ is a measure of small business and farm lending normalized by total assets in 2022H1; $PROB22$ is a bank's aggregate measure of past-due and non-accrual loans relative to total assets in 2022H1; and $SMALLBANK$ and $MIDBANK$ are indicator variables for small and medium-sized banks, respectively. All columns are instrumental variable regressions. Columns 2 includes weighted least squares specifications. Columns 3, 4, and 5 represent the sample of small, medium, and large banks respectively. Standard errors in parentheses are clustered by bank size.

of SME exposure after the PPP program was ended. They then moved over the final year of our sample to rebalance that exposure away from SME lending.

However, the apparent discrepancy between the results for our PPP and $PPPLF$ variables of interest and our conditioning variable for SME exposure going into the last year of our sample is notable. The insignificance of the share of SME loans going into the sample suggests a lack of evidence that bank SME lending growth responded similarly to higher average levels of SME exposure per se. Instead, high shares of SME lending going into this period likely reflect SME-intensive bank lending strategies which were independent of the heightened SME exposure related to the PPP program. As such, while banks did not necessarily perceive a high amount of SME lending as being excessive, elevated PPP program participation at the outset of the pandemic appears to have encouraged expanded SME lending beyond desired levels. They then appear to have responded with reduced SME exposure associated with great participation in these programs.[29]

Overall, our results suggest that the incentives associated with the PPP and PPPLF programs induced banks to move away from their desired SME exposure levels, as our negative estimated coefficients on PPP and $PPPLF$ over the last year of our sample demonstrated banks' efforts to reduce these exposure levels. Of course, our positive results found for our full time series sample demonstrates that while banks moved to reduce their outsized SME exposures after the waning of the PPP and PPPLF programs, the earlier increases in SME lending associated with participation in these programs were not completely reversed. Instead, we observe a persistent increase in SME exposure associated with participation in both programs over the 3.5 year sample.

VII. Conclusion

This paper examines growth in SME lending by US commercial banks from the beginning of the pandemic period through the first half of 2023, a time by which exposure to PPP loans were essentially eliminated. We find persistent and economically important increases in bank SME lending related to participation in both the PPP and PPPLF programs over this period. Our point estimates indicate that a one standard deviation increase in PPP participation and a one standard deviation increase in PPPLF participation increases average annual growth in SME lending by 3.8 and 4.9

[29]This conjecture is supported by the fact that the correlations between $SME22H1$ and PPP and $PPPLF$ are very small at 0.07 and -0.06 respectively, so levels of SME exposure going into this period were largely independent of PPP participation.

percentage points respectively. This results in large cumulative increases that appear to outlast the programs.

Our findings are driven by small and medium-sized banks, as both showed statistically significant positive dependence on instrumented PPP and PPPLF participation, while large bank SME lending exposure growth was not significantly related to participation in either program. We therefore conclude that the persistent effects of the PPP program on SME lending were limited to small and medium-sized banks. These results also illustrate the importance of including small and medium-sized banks in assessing the implications of programs targeted towards encouraging SME lending. Available information on those banks' lending is more limited, as in our use of Call Report data in this study. In this study, small and medium-sized banks not only were significant lenders to SMEs in aggregate, but they also exhibited notably distinct responses to the PPP and PPPLF programs compared to the larger stress-tested banks covered in Y-14 and other data sets.[30]

We characterize the impact as persistent, rather than permanent, based on our findings for SME lending growth over the last year of our sample, by which exposure to PPP funds had largely been exhausted. Our results for this later period show that banks that had exhibited increased PPP and PPPLF participation at the height of the pandemic significantly reduced their SME exposure levels. It appears that both programs induced banks to expand their SME lending exposure beyond desired levels, and they responded to the end of the program by rebalancing that exposure to desired levels.

Still, the increase in exposure associated with program participation appears to have outlasted the PPP and PPPLF programs themselves. As such, our results have implications for the formation of banking relationships. Since the PPP loans were guaranteed, banks had no incentive to acquire information about the creditworthiness of their borrowers. However, our finding that SME lending remained elevated after the exhaustion of the PPP program suggests that while banks moved to reduce the excess SME exposure they acquired during the pandemic associated with the PPP and PPPLF programs, the net impact of the programs was an increase in SME exposure. As it is possible that the drawdown of SME exposure will continue until the gains associated with program participation are eventually eliminated, we would characterize this response as "persistent," rather than "permanent." However, we do find

[30]A substantial share of SME lending comes from non-stress tested banks, 99% percent in our sample.

that for the final half year of our sample there is no apparent relationship between PPP and PPPLF participation and SME lending. This suggests that the drawdown in SME exposure was largely concluded by the end of our sample, leaving an economically and statistically significant increase in SME lending associated with PPP and PPPLF program participation.

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Table A1. Changes in Specification

	Drop Covariates	Total Capital	Lag %ΔSME	%ΔSMEPPP	%ΔSMELT	HighPPP
PPP	0.716***	0.828***	0.885***	2.412***	0.188**	
	(0.0630)	(0.0841)	(0.0770)	(0.0710)	(0.0695)	
SMALLBANK	-0.0190***	0.0142***	0.00479*	-0.0880***	0.0369***	0.0121***
	(0.000619)	(0.00181)	(0.00226)	(0.0181)	(0.00301)	(0.000239)
MIDBANK	-0.0333***	-0.0197***	-0.0254***	-0.0911***	0.0144***	-0.0296***
	(0.00145)	(0.00105)	(0.000670)	(0.00502)	(0.00262)	(0.00409)
LIQUID		0.149***	0.120***	0.225***	0.0202*	0.166***
		(0.0162)	(0.0175)	(0.0251)	(0.00898)	(0.00911)
COMMIT		-0.256**	-0.267**	-0.164	-0.0333	-0.316***
		(0.0792)	(0.100)	(0.205)	(0.0485)	(0.0316)
DEPOSITS		-0.0278	-0.0278	-0.0917*	0.0154	-0.0534***
		(0.0274)	(0.0280)	(0.0444)	(0.0181)	(0.0121)
CAPRAT		0.0436**				
		(0.0157)				
SME19H2		-0.389***	-0.359***	-0.786***	-0.121***	-0.365***
		(0.00182)	(0.00218)	(0.0700)	(0.0226)	(0.000598)
PROB		0.0962***	0.0532	0.00828	0.0465	0.239***
		(0.0265)	(0.0384)	(0.0928)	(0.0250)	(0.0476)
%ΔSME18			0.0115***			
			(0.000721)			
TIER1CAP			0.0352***	0.107***	-0.0369**	0.140***
			(0.00980)	(0.00142)	(0.0125)	(0.0291)
HIGHPPP						0.119***
						(0.0196)
CONSTANT	0.0648***	0.108***	0.108**	0.300***	0.00199	0.0835**
	(0.00247)	(0.0323)	(0.0334)	(0.0471)	(0.0231)	(0.0265)
N	4143	4079	4033	4079	4105	4079

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Column 1 drops all covariates. Column 2 replaces $TIER1CAP$ with $TOTCAP$, a measure of a bank's total capital. Column 3 includes %ΔSME18, lagged growth in SME lending 2018H2 to 2019H2. Column 4 replaces $\%\Delta SME$ with $\%\Delta SMEPPP$, average annualized growth in the sum of SME lending and PPP lending between 2019H2 and 2023H1. Column 5 replaces dependent variable $\%\Delta SME$ with $\%\Delta SMELT$, cumulative growth in SME lending between 2019H2 and 2023H1. Column 6 replaces PPP with $HIGHPPP$, equal to 1 if a bank's PPP value is greater than the median value and 0 otherwise.

TABLE A2. Changes in Sample

	Truncate	1-99	9-95	DFAST	NONDFAST
PPP	0.809***	1.021***	0.880***	8.199	0.853***
	(0.158)	(0.0424)	(0.0877)	(4.498)	(0.168)
LIQUID	0.0126	0.240***	0.0790***	2.239***	0.123***
	(0.0145)	(0.0169)	(0.0129)	(0.570)	(0.0366)
COMMIT	-0.175***	-0.356***	-0.296***	-0.392	-0.322**
	(0.0128)	(0.0676)	(0.0681)	(0.931)	(0.124)
DEPOSITS	0.000855	-0.0385***	-0.0128	-0.298	0.0144
	(0.0249)	(0.00301)	(0.0222)	(0.929)	(0.0455)
TIER1CAP	0.0831***	0.163***	0.0283*	1.810	0.109**
	(0.0225)	(0.00557)	(0.0125)	(1.362)	(0.0416)
SME19H2	-0.242***	-0.547***	-0.306***	-0.707	-0.336***
	(0.00334)	(0.00829)	(0.000168)	(0.979)	(0.0236)
PROB	-0.0567	0.256***	0.130***	7.773	0.0952
	(0.0343)	(0.0207)	(0.0114)	(5.114)	(0.150)
SMALLBANK	-0.000799	-0.0173***	0.00466***		
	(0.00377)	(0.00236)	(0.000796)		
MIDBANK	-0.0201***	-0.0617***	-0.0180***		
	(0.00474)	(0.000203)	(0.00162)		
CONSTANT	0.0651*	0.154***	0.0853**	-0.276	0.0618
	(0.0274)	(0.00954)	(0.0266)	(0.671)	(0.0403)
N	3929	4079	4079	30	4049

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Column 1 truncates our base specification data set at 2.5%-97.5%. Column 2 winsorizes at the 1%-99% level. Column 3 winsorizes at the 5%-95% level. Column 4 reduces the sample to DFAST banks only. Column 5 reduces the sample to NONDFAST banks only.

Table A3. Changes in Estimation

	OLS	Standard SE	Robust SE	Region Cluster	TOBIT	SME Share Weight
PPP	1.200**	0.864***	0.864***	0.864***	1.200***	1.439***
	(0.0107)	(0.166)	(0.176)	(0.0934)	(0.234)	(0.176)
LIQUID	0.116*	0.131***	0.131**	0.131*	0.116	0.325***
	(0.00374)	(0.0361)	(0.0464)	(0.0569)	(0.0688)	(0.0484)
COMMIT	-0.441	-0.246*	-0.246	-0.246	-0.441***	-0.716***
	(0.177)	(0.125)	(0.136)	(0.166)	(0.0833)	(0.128)
DEPOSITS	-0.0462	-0.0180	-0.0180	-0.0180	-0.0461	-0.185***
	(0.0203)	(0.0458)	(0.0516)	(0.0432)	(0.0513)	(0.0511)
TIER1CAP	0.0823	0.0679	0.0679	0.0679	0.0824	-0.0401
	(0.0153)	(0.0428)	(0.0561)	(0.0581)	(0.0852)	(0.0218)
SME19H2	-0.365**	-0.379***	-0.379***	-0.379***	-0.365***	-0.212***
	(0.00555)	(0.0253)	(0.0282)	(0.0145)	(0.0195)	(0.0298)
PROB	0.121	0.0864	0.0864	0.0864	0.121	0.472***
	(0.0311)	(0.150)	(0.160)	(0.161)	(0.145)	(0.118)
SMALLBANK	-0.00306	0.00950	0.00950	0.00950	-0.00306	-0.0426***
	(0.00622)	(0.0164)	(0.0195)	(0.0242)	(0.0247)	(0.00128)
MIDBANK	-0.0328*	-0.0223	-0.0223	-0.0223	-0.0328	-0.0384***
	(0.00241)	(0.0162)	(0.0188)	(0.0220)	(0.0226)	(0.00266)
CONSTANT	0.117	0.0956*	0.0956*	0.0956*	0.117*	0.218***
	(0.0313)	(0.0407)	(0.0472)	(0.0470)	(0.0521)	(0.0191)
var(e.%ΔSME)					0.0210***	
					(0.00248)	
N	4308	4079	4079	4079	4307	4079

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Column 1 uses OLS estimation. Column 2 replaces clustered SEs with standard SEs. Column 3 replaces clustered SEs with robust SEs. Column 4 clusters by region using the 4 standard regions of the U.S.: Northeast, South, Midwest, and West. Column 5 uses tobit estimation. Column 6 weights by SME share.