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

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Abstract. We examine the longer-term effects of the Paycheck Protection Program (PPP) and the PPP Liquidity Facility (PPPLF) on small business (SME) lending using bank-level Call Report data. To identify a causal impact, we instrument for PPP and PPPLF lending based on pre-existing relationships with the Small Business Administration and the Federal Reserve discount window. Elevated bank participation in both programs is positively associated with a substantial increase in average SME lending growth lasting long after banks exposures to PPP loans had been largely eliminated. Splitting samples by size, PPP participation persistently increased SME lending by large and small banks, but persistent PPPLF program effects were limited to small banks. Our results suggest that the PPP fostered SME banking relationships, despite the reduced incentives for forming such relationships under government lending guarantees.

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JEL classification: E58, E63, G14, G18, G32

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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) had greater exposure to disruptions from pandemic-related lockdowns due to their prevalence in service sectors, including retail and food services (Bowman (2020)). The program was administered by the Small Business Administration (SBA) and allowed qualified SMEs 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 (Pandemic Response Accountability Committee (2024)).[2]

The program was controversial. Analysts have argued that the involvement of commercial banks distorted the allocation of funds.[3] Moreover, some find that the employment benefits of the program were modest relative to its cost (e.g. Granja et al. (2022)). Studies also indicate that the majority of funds extended went to business owners and shareholders, rather than employees (e.g. Autor et al. (2022)).[4] However, the desire to distribute PPP funds quickly, combined with the use of direct commercial bank lending likely contributed to their finding that the distribution of PPP funds were poorly correlated with the intensity of distress geographically. Moreover, given sufficient costs to delays in distributing funds, even programs with poor targeting may improve welfare (e.g. Bartik et al. (2020)).

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

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

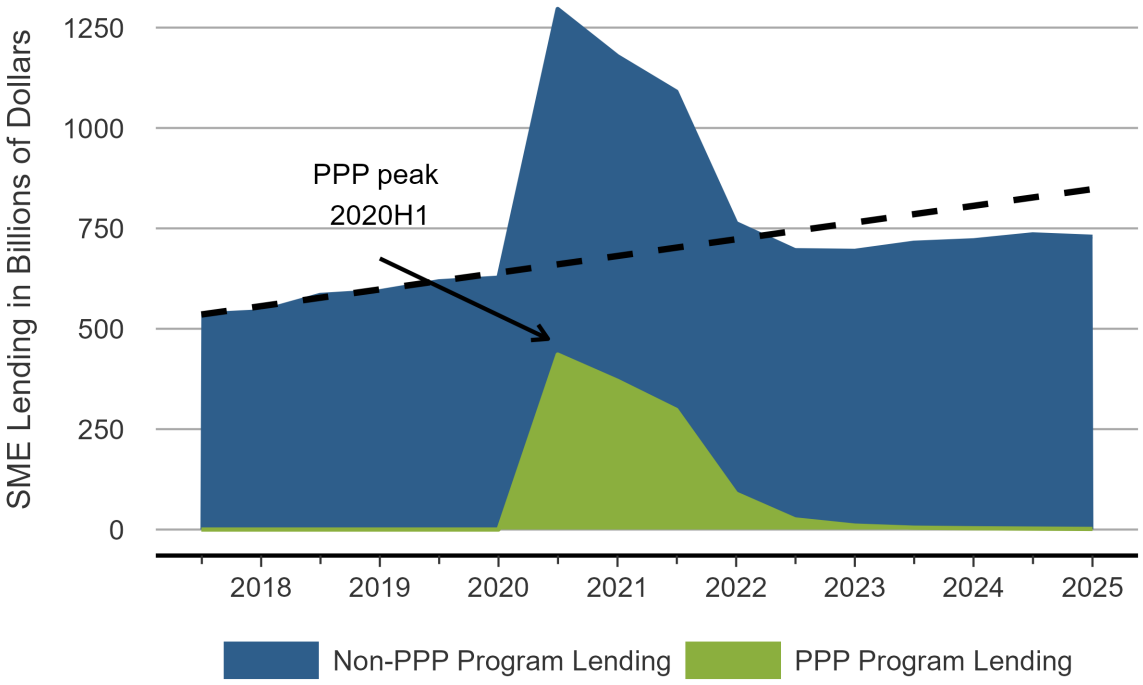
[2]Data as of October 2023. As of that date, 10.6 million of the 11.5 million loans extended under the PPP program had been forgiven.

[3]For example, Chernenko and Scharfstein (2024) find that black-owned enterprises were less likely to receive PPP loans from banks than non-bank lenders.

[4]Other studies are more positive. Joaquim and Netto (2021) estimate that the program saved 7.5 million jobs, while Splinter et al. (2024) argue that properly accounting non-wage costs borne by employers suggests that 55% of PPP funds went to workers.

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 (2023), and Marsh and Sharma (2024)). Moreover, Joaquim and Wang (2022) show that receiving PPP loans improved firm financial conditions while Agarwal et al. (2024) find that participation in the PPP reduced mortgage delinquency.

FIGURE 1. Total Small Business Bank Lending 2017H1-2024H2



Note: Total SME and PPP program lending. Dashed trend line represents average annual growth in SME lending from 2017H1 to 2019H2.

The positive impact of the PPP on lending can be seen in Figure 1. Figure 1 shows total commercial bank PPP and conventional SME lending, as reported in regulatory filings in the Call Report, from 2017H1 through 2024H2.[5] It can be seen that SME lending grew dramatically during the pandemic. At the end of 2019, total SME lending had grown to 641 billion dollars. SME lending increased markedly with 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)].

[5]Data is measured at end of period and is biannual. Many smaller institutions only submit reports on SME lending in the second and fourth quarters of each year.

However, the out-sized SME lending 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 commercial bank PPP lending reported in the Call Report having fallen from a high of over $447 billion at 2020H1 to about $1 billion at 2024H2. This figure is modestly below that which would be implied by pre-pandemic growth (dashed line).

In this paper, we investigate the persistent SME lending impact of the PPP and PPPLF programs. Despite rapid growth in exposure due to program lending, the impact on conventional SME lending is less clear. Banks that were planning on extending loans to SMEs may have preferred to substitute 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, or alternatively gained general expertise in SME lending as a result of participation in the program, the increased exposure to SMEs may have outlasted these programs.

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, while Chodorow-Reich et al. (2022) find using a sample of stress-tested large banks that PPP and conventional SME lending behaved as substitutes during the pandemic. Filomeni (2024) shows that community banks responded to participation in the PPP program with greater reductions in conventional lending risk than large and medium-sized banks.

We investigate the persistent impacts of participation in these programs on SME lending, up to the end of 2024. By that date, almost all PPP debt had been repaid, or in most cases, forgiven.[6] As reporting to the Call Report is compulsory for all U.S. banks, our study includes small and medium-sized U.S. banks not included in the sample of stress-tested larger banks in Y-14 data. These small and medium-sized banks are important sources of SME lending, and as shown below, responses to the PPP and PPPLF programs differed substantively by bank size.

Our dependent variable is the average annualized percentage growth in biannual conventional SME lending (excluding PPP loans) from 2019H2 through 2024H2. Our

[6]Because many PPP loans had 5 year maturities, banks did have modest residual PPP exposure at 2024H2 totaling $1 billion. This value pales in comparison with the $447 billion in PPP loans at our sample peak at 2020H1.

variable of interest 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. Moreover, the PPP program was not over-subscribed in later rounds, which would introduce another set of heterogeneity compared to the programs during the pandemic period.

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. Moreover, this instrument is likely to be informative, as PPP lending was greater in areas with greater SBA exposure in 2019 (see Liu and Volker (2020)). Our posited exclusion restrictions for these instruments are likely to be valid as the geographic patterns of PPP lending was less correlated with the economic conditions under the pandemic (Granja et al. (2022)). We consider two indicators of pre-existing SBA ties: 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 use indicators of preparedness for Federal Reserve discount window borrowing. As the Federal Reserve administered the PPPLF program, additional preparedness for discount window borrowing is likely to indicate better-preparedness 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.

[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.

Our results demonstrate that SME lending growth over the extended period was positively correlated with bank participation in the PPP program during the pandemic, even though outstanding PPP loans had fallen close to zero by the end of our sample. Our full-sample base specification coefficient estimates suggest that a one standard deviation increase in our instrumented PPP participation measure is associated with a 2.0 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 an 2.6 percentage point increase in average annual SME lending growth over our sample period.

However, our analysis also demonstrates notable discrepancies in the responses to program participation by bank size. Separating our sample into small, medium, and large bank sub-samples, we identify positive and statistically and economically significant relationships between PPP lending during the pandemic and cumulative growth in SME lending over our sample period for both small and large-sized banks, while the impact on cumulative SME lending growth by medium-sized banks is insignificant. Our finding of a positive impact on persistent SME lending growth for large banks is sufficient to also yield an economically and statistically significant positive estimate for the impact of PPP lending during the pandemic on persistent lending growth for our full sample weighted by bank size.

SME lending responses to PPPLF program participation also differ by bank size. The PPPLF was primarily designed to mitigate the potential adverse liquidity implications of small banks participating in the PPP program [e.g. Bowman (2020)]. It is therefore not surprising that we find small banks' cumulative lending patterns disproportionately respond positively to participation in the PPPLF program: We obtain significant positive responses in cumulative SME lending to PPPLF participation for our small bank sub-sample, but our results for both medium and large bank sub-sample responses to PPPLF participation are insignificant. Our results for PPPLF participation also enter significantly negative for our full sample weighted by bank size.

Finally, we investigate whether banks drew down their expanded SME exposure associated with these programs once the incentives associated with the PPP and the PPPLF were removed. We rerun our specification for a sample beginning in 2022H1, after the funds associated with the PPP program had largely been forgiven or repaid. Our full sample results suggest that higher PPP participation by banks

did restrain SME lending after the programs had ended. We obtain a significantly negative relationship between participation in both the PPP and PPPLF programs and SME lending growth during this post-program period.

We also find substantive disparities in the responses in SME lending growth over this latter period by bank size. Increased PPP participation led to greater reductions in SME lending at economically and statistically significant levels on average only among small banks whose pandemic-related increases in SME exposure due to heightened PPP participation likely had the largest impacts on SME balance sheet shares. In contrast, pandemic-era PPP participation had insignificant impacts on both medium-sized and large banks over this latter period, suggesting that medium and large banks were more willing to maintain their elevated SME lending associated with the PPP program. Similarly, while we obtain negative point estimates over this latter period for the impact of PPPLF participation on SME lending growth for all bank size subgroups, only our small bank subgroup enters at statistically significant levels.

Despite this retrenchment at the end of our sample, our full period results indicate that on average the negative impacts of the programs on SME lending after they had ended were insufficient to fully offset the earlier gains, resulting in net increases in SME lending growth for the entire sample period associated with pandemic PPP participation. This persistence is somewhat surprising. The prevailing literature on banking relationships suggests that relationships conventionally emerge as the product of costly information gathering or monitoring [e.g. Diamond (1984), Allen (1990), and Boot and Thakor (2002)]. Berger et al. (2024) find that the hard and soft information gathered through conventional lending impacts terms faced on so-called “transactions lending," in this case credit card lending, which 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, the persistent effects of PPP program participation for all banks, and for PPPLF participation for small banks on SME lending after the programs had ended, suggests that some relationship formation with SME borrowers did arise, despite the apparent lack of an incentive for banks to acquire costly information on individual SME borrowers.

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 full-sample results for both PPP and PPPLF participation. Section 6 then repeats our specification for our late-sample. Lastly, section 7 concludes.

II. 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 were guaranteed under the program to assist firms in servicing payroll costs and other 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 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 the 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

[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).

PPP loan terms. In the event of loan forgiveness, default or 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 application process itself yielded little tangible information about successful PPP applicants. 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 application did include substantive questions concerning outstanding delinquencies, bankruptcies, and the incarceration histories of owners. However, improper responses to these questions immediately barred the applicant from PPP loan approval. New information obtained from the PPP application only covered ownership of additional businesses, prior receipt of COVID-related SBA disaster lending, the firm's franchise status, and whether employees were predominantly located in the United States.

III. Data

Our sample is a cross-section of U.S. commercial banks. Our main dataset is 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, and measured as of end of period.[12] We use 2019H2 data to characterize bank conditions going into the 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 loan exposure.

To be included in the sample, banks must have reported some level of SME lending in the Call Report in 2019H2. Reporting banks are separated into three categories based on asset size at that time. Our designations follow Call Report conventions,

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

[12]We limit our analysis to these quarters as Call Report coverage is incomplete during quarters 1 and 3, particularly for small bank SME lending reporting.

with small banks defined as those with assets below $10 billion, large banks with assets exceeding $100 billion, and medium-sized banks between. Our base specification sample contains 3,960 banks, of which 3,852 are classified as small banks, 83 as medium-size banks, and 25 as large banks. We also adopt the Call Report definition of conventional small business and farm lending as business loans of $1 million or less and farm loans of $500,000 or less, respectively, including drawdowns on loan commitments.

We characterize PPP and PPPLF program participation through the variables PPP and $PPPLF$. PPP is defined as the ratio of PPP loan volume outstanding, as per Call Report filings, to total assets.[13] $PPPLF$ is defined as the ratio of bank borrowing from the PPPLF program relative to total SME lending, including PPP borrowing.[14] To remove the influence of outliers and reporting errors, we winsorize our base specification data set at the 2.5%-97.5% level.[15]

The aggregate evolution of SME and PPP lending from 2019H2 to 2024H2 is summarized in Table 1. Following the introduction of the PPP program during the first half of 2020, SME lending experiences a pronounced increase due to the high number of PPP loans. However, the sub-sample of 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 2024H2, outstanding PPP loan exposure is almost reduced to zero. Conventional SME lending is lower than 2020H1 levels as well, but 2024H2 levels of conventional lending are higher than those at the end of 2022H1, confirming that SME lending has resumed its growth at close to trend levels.

[13]Call Report reporting is compulsory for regulated banks, so there are no endogeneity issues in bank 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.

[14]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.

[15]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 winsorizing at the 0.1%-99.0% or 0.5%-95.0% levels (Table A2).

TABLE 1. SME and PPP Lending (2019H2-2024H2)

Sample	Lending	2019H2	2020H1	2022H1	2024H2
FULL	SME	6.27	8.61	6.70	7.28
	PPP	0.00	4.36	0.25	0.01
	TOTAL	6.27	12.97	6.95	7.29
SMALL	SME	3.00	4.14	3.33	3.57
	PPP	0.00	1.81	0.09	0.01
	TOTAL	3.00	5.95	3.42	3.58
MID	SME	1.02	1.52	1.12	1.07
	PPP	0.00	1.06	0.06	0.00
	TOTAL	1.02	2.58	1.18	1.07
LARGE	SME	2.25	2.94	2.25	2.63
	PPP	0.00	1.50	0.10	0.00
	TOTAL	2.25	4.44	2.35	2.63

Note: Levels of SME and PPP lending in hundreds of billions of dollars. SME lending refers to conventional small business and farm lending. PPP lending is PPP loan volume outstanding, as per Call Report filings. Total lending is the sum of conventional SME and PPP lending. 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 2024H2, show lending two and 3.5 years after the peak of the program respectively.

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 2024H2.

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 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 panel banking data (e.g. Cornett et al. (2011)).

Our conditioning variables include $LIQUID$, which measures bank cash and security holdings as a share of total assets as a measure of bank liquidity; $DEPOSITS$, which measures core deposits relative to total assets to capture a bank's reliance on deposit funding; $TIER1CAP$, 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 also include $SME19H2$, a

measure of levels of SME lending normalized by total assets in 2019H2 to account for existing disparities between banks in small business exposure prior to the pandemic, and $PROB$ as an aggregate measure of past-due and non-accrual "problem" loans relative to total assets. Finally, we include $TRADABLE$ as the share of available for sale assets held by banks to identify differences in bank business models.

Summary statistics for our dependent variables and explanatory variables of interest under our base specification sample are shown in Table 2.[16] Our sample exhibits a large amount of variability across banks, with the standard deviation of average annual growth in SME lending far higher than the mean value for that variable for all samples.

It can also be seen that mean values for all bank size groups for our dependent variable, $\%\Delta SME$, 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. Shares of SME lending exposure going into the pandemic ($SME19H2$) were highest among small banks and lowest among large banks, with average small bank exposure as a share of total assets 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 their existing web presences to attract firms under the PPP program due to their ease of application and the associated ability to distribute funds quickly [Lopez and Spiegel (2023)].

IV. Estimation

IV.1. **Identification.** Bank participation in the PPP and PPPLF programs is likely endogenous to the impact of the COVID-19 pandemic on bank fundamentals. In response, 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

[16]Summary statistics for the conditioning variables are shown in Online Appendix Table OA.1. Small banks display the highest mean and median capital levels, as measured by tier 1 capital. This is notable, as it suggests that the greater responsiveness to program participation we observe among small banks below is not attributable to greater regulatory constraint.

TABLE 2. Summary Statistics by Bank Size

SAMPLE		N	Median	Mean	SD	Min	Max
FULL	$\%\Delta SME$	3,960	0.042	0.067	0.115	-0.104	0.513
	$\%\Delta SME22$	3,960	0.032	0.045	0.105	-0.162	0.402
	PPP	3,960	0.040	0.051	0.044	0.000	0.189
	$PPPLF$	3,960	0.000	0.025	0.078	0.000	0.340
	$SME19H2$	3,960	0.166	0.179	0.101	0.001	0.435
SMALL	$\%\Delta SME$	3,852	0.042	0.067	0.114	-0.104	0.513
	$\%\Delta SME22$	3,852	0.033	0.047	0.104	-0.162	0.402
	PPP	3,852	0.040	0.051	0.044	0.000	0.189
	$PPPLF$	3,852	0.000	0.025	0.077	0.000	0.340
	$SME19H2$	3,852	0.169	0.182	0.099	0.000	0.435
MID	$\%\Delta SME$	83	0.038	0.056	0.117	-0.104	0.513
	$\%\Delta SME22$	83	-0.024	-0.006	0.119	-0.162	0.402
	PPP	83	0.049	0.047	0.031	0.000	0.189
	$PPPLF$	83	0.000	0.042	0.107	0.000	0.340
	$SME19H2$	83	0.048	0.056	0.043	0.000	0.186
LARGE	$\%\Delta SME$	25	0.049	0.086	0.181	-0.104	0.513
	$\%\Delta SME22$	25	-0.001	-0.008	0.133	-0.162	0.402
	PPP	25	0.010	0.016	0.017	0.000	0.053
	$PPPLF$	25	0.000	0.010	0.050	0.000	0.248
	$SME19H2$	25	0.017	0.028	0.046	0.001	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 2024H2; $\%\Delta SME22$ is average annualized growth in SME lending from 2022H1 through 2024H2; 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 small business and farm lending (including PPP lending) in 2020H1. $SME19H2$ is conventional SME normalized by total assets in 2019H2.

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:

$$SBA_i = \frac{SBALEND_i}{SME_i}. \tag{1}$$

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, $INDMIX_i$ satisfies

$$INDMIX_i = \sum_j \left(\frac{SBA_j}{SBA} \cdot \frac{BUSF_{i,j}}{BUSF_i} \right), \tag{2}$$

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, prior to the onset of the pandemic. 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 two indicators of familiarity with the Federal Reserve discount window, as the Federal Reserve administered the PPPLF. Our measures are 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 ($COLLATERAL_i$). Both values are again calculated at 2019H2, prior to the onset of the pandemic and the PPP and PPPLF programs.

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 (Anbil et al. (2023)).[17] Relative values of these instrumental variables should also influence PPP 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.

IV.2. **Second-stage specification.** 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.

To identify a causal relationship, we use instrumental variables estimation. As PPP and $PPPLF$ are highly correlated, we examine the impact of participation in each program separately in our base specifications.[18]

Our dependent variable is $\%\Delta SME_i$, the average annual growth in a bank's small business and farm lending from 2019H2 through 2024H2. The second stage of our two-stage least squares specification for the impact of PPP participation satisfies:

$$\%\Delta SME_i = c + \beta_1 PPP_i + \beta X_i + \beta_2 SMALL_i + \beta_3 MED_i + \epsilon_i \tag{3}$$

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, we cluster our standard errors by bank size. Large banks face different funding and lending opportunities than small or medium-sized banks. 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. In response, we cluster our standard errors by bank size.

We then repeat our base specification for the three bank size sub-groups separately, with White heteroscedasticity-robust standard error estimation. To allow for the

[17]As this data is proprietary to the Federal Reserve, it is not publicly available.

[18]The correlation coefficient between our measures of PPP and PPPLF program participation in our base sample is 0.41. Including both instrumented PPP and PPPLF participation variables in our specification results in the PPP variable entering measurably positively and the $PPPLF$ variable entering measurably negatively. These results can be found in Appendix Table A1

elevated importance of large bank lending growth for the aggregate response of SME lending to the PPP program, we also report the results for the full sample using weighted least squares, with observations weighted by bank total assets.

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

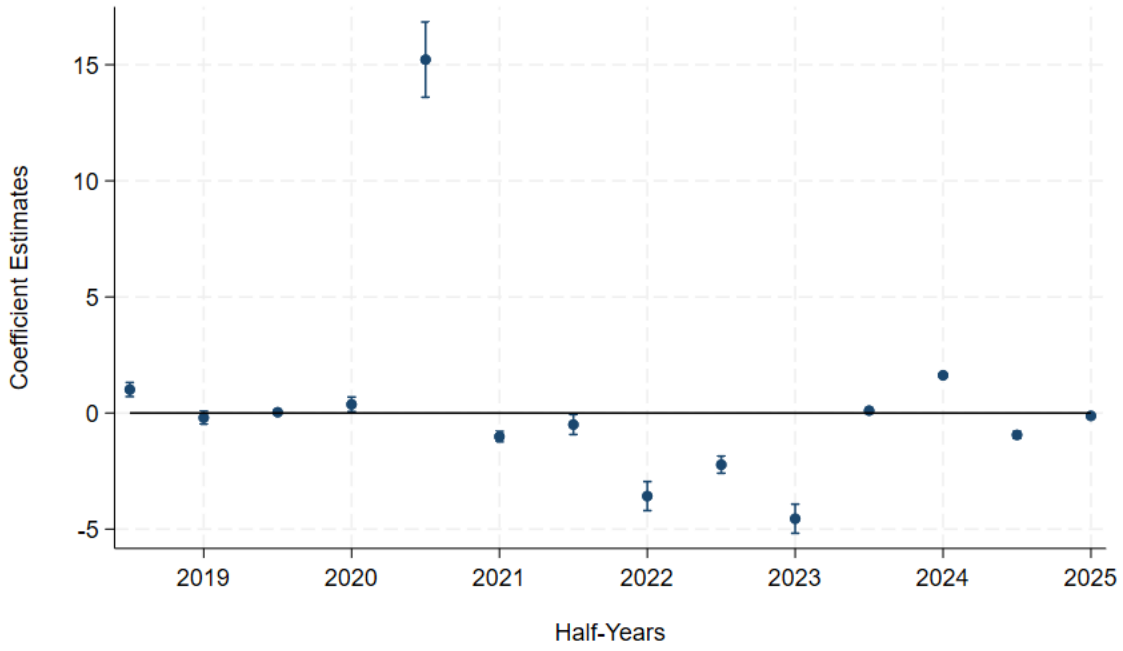
$$\%\Delta SME_i = c + \beta_1 PPPLF_i + \beta X_i + \beta_2 SMALL_i + \beta_3 MED_i + \epsilon_i \tag{4}$$

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 our sample separated into small, medium, and large bank sub-samples and with weighted least squares.

IV.3. **Half-year univariate results.** We first demonstrate that the impact of our instrumented variable of interest directly reflects the launch of the PPP program (and that the instrumented PPP variable has the expected contemporaneous impact on SME lending), rather than spurious correlations with existing bank-specific characteristics prior to the pandemic. 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]

[19]The regression results for these univariate half-year regressions are reported in online appendix table OA.2. Standard errors are clustered by bank size, as in our base specification.

FIGURE 2. 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 2024H2. Standard errors are clustered by bank size. Bars represent 95% confidence intervals.

Our results are shown in Figure 2. Reassuringly, PPP participation in 2020H1 has no significant effect on SME lending growth prior to the pandemic. Our coefficient point estimates prior to our intervention date are all small relative to the point estimate on the date of the intervention. While some are statistically significant, 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.

We do observe a very large contemporaneous impact of PPP participation in the half-year ending in 2020H1 on SME lending, as would be expected. Our point estimate suggests that a one standard deviation increase in PPP participation was associated with an 78 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, some of which

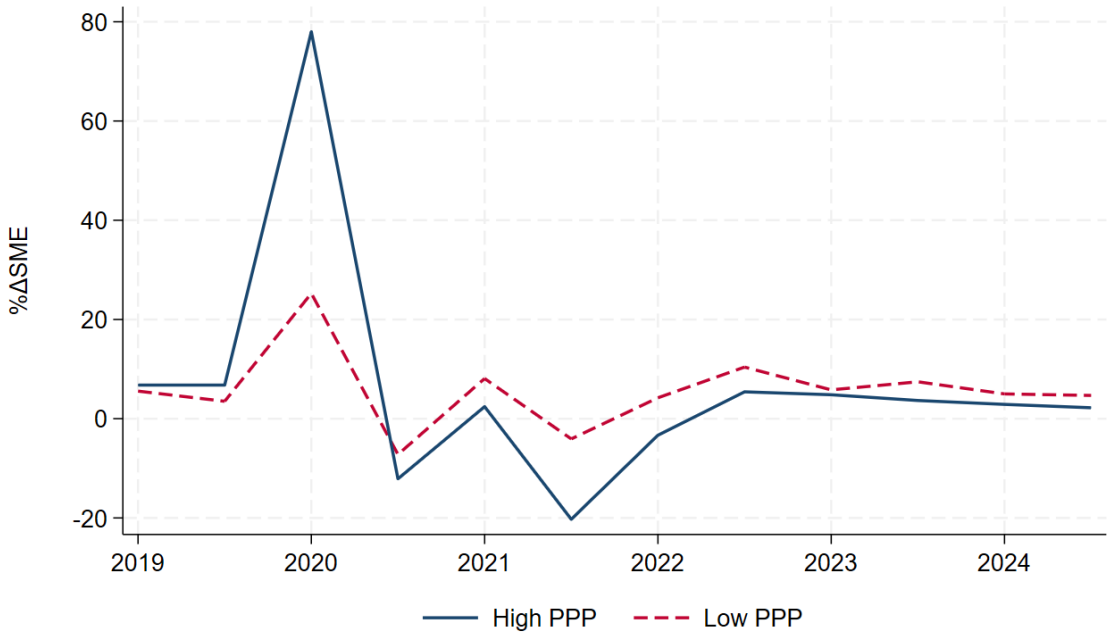
are statistically significant. As we discuss below, these negative values likely reflect bank efforts to correct out-sized increases in SME lending growth in 2020H1 attributable to PPP program participation. However, these declines are far smaller than the large spike in 2020. The net result is therefore 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 2020H1, as measured by our PPP variable.

Figure 3 plots average 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. 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.

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. The average value of $\%\Delta SME$ is equal to 77% for the high PPP group and 25% for the low PPP group. However, after the intervention period the low PPP group exhibits modest but consistently higher growth in SME lending, suggesting that a portion of the outsized growth for high-PPP firms during the expansion period was reversed over the remainder of our sample.

FIGURE 3. High vs. Low PPP Participation in SME Lending



Note: Average annualized percentage changes in half-year SME lending growth rates for above and below median PPP participation banks in 2020H1.

V. RESULTS

V.1. **PPP participation and lending growth.** Our full-sample base IV specification results for PPP participation are shown in Table 3, 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 2.0 percentage point increase in average annual SME lending growth.

We also evaluate the strength of our instruments. Our Cragg-Donald Wald F statistic is 127.75, which passes the Stock-Yogo weak identification test at a 5% confidence level. Our base results also obtain an Anderson LM statistic of 454.03, 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 10.59 and an AR statistic of 18.93, both of which reject weak instruments at a 1% confidence level.[20]

[20]We report the results for the first stage of the regressions in online appendix Table OA.5.

TABLE 3. PPP and Small Business and Farm Lending

	Full	Small	Medium	Large	WLS
PPP	0.457***	0.455***	-0.480	10.43***	1.680***
	(0.00967)	(0.140)	(5.572)	(3.337)	(0.374)
LIQUID	0.0863***	0.0674*	-0.742	1.708***	1.159***
	(0.00496)	(0.0357)	(0.752)	(0.454)	(0.114)
COMMIT	-0.215***	-0.195*	-1.019	-0.465	-1.132***
	(0.0111)	(0.106)	(0.930)	(0.532)	(0.125)
DEPOSITS	0.00876	0.0318	-0.328	-1.376*	-0.360***
	(0.0172)	(0.0423)	(0.289)	(0.810)	(0.0629)
TIER1CAP	0.123***	0.146***	-1.185***	2.539	-0.711***
	(0.0164)	(0.0482)	(0.531)	(2.008)	(0.138)
SME19H2	-0.222***	-0.222***	-0.569	0.151	-0.361***
	(0.00112)	(0.0199)	(1.739)	(0.297)	(0.0420)
PROB	0.0907***	0.0883	-0.998	10.80***	-0.0230
	(0.00951)	(0.125)	(1.301)	(3.039)	(1.226)
TRADEABLE	-0.0403***	-0.0474***	0.203	1.213***	0.225***
	(0.00356)	(0.0182)	(0.219)	(0.423)	(0.0257)
SMALLBANK	-0.0233***				-0.0256**
	(0.00163)				(0.0104)
MIDBANK	-0.0428***				-0.00269*
	(0.000593)				(0.00156)
CONSTANT	0.0825***	0.0383	0.609*	0.131	0.379***
	(0.0158)	(0.0377)	(0.370)	(0.365)	(0.122)
N	3960	3852	83	25	3960

Note: IV estimation with dependent variable $\%\Delta SME$, average annualized growth in small business and farm lending between 2019H2 and 2023H1. PPP is 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; $TRADABLE$ is the share of tradable assets; and $SMALLBANK$ and $MIDBANK$ are indicator variables for small and medium-sized banks, respectively. See text for instruments used for PPP. Columns 2, 3, and 4 represent the sample of small, medium, and large banks respectively. Column 5 estimated by weighted least squares, with observations weighted by total assets. Standard errors in parentheses are clustered by bank size. Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

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 $COMMIT$, $SME19H2$, and $TRADABLE$, indicating less SME lending growth on average for banks with greater outstanding loan commitments, greater existing exposure to SME lending, and higher shares of tradable assets. $DEPOSITS$ enters insignificantly.[21]

Lastly, our indicator variable for the small and medium-sized bank groups enter negatively, while our constant term enters positively, again all at 1% confidence levels. These results imply that the impact of PPP program participation on persistent SME lending growth is highest on average among large banks, followed by small banks, and then medium-sized banks.

Columns 2, 3, and 4 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 large-sized banks, but PPP enters insignificantly for our medium bank sub-sample. Our instrument diagnostics for the small bank sub-sample also reject weak instruments, with the Cragg-Donald Wald F passing the Stock-Yogo weak identification test at a 5% confidence level, and our Montiel-Pflueger CLR and AR statistics rejecting weak instruments at a 1% confidence level.[22] However, these statistics fail to reject weak instruments for our medium-sized bank sub-sample, and we obtain mixed results for our large bank sub-sample, with our CLR statistic rejecting weak instruments at a 5% confidence level but our Cragg-Donald and AR statistics failing to reject weak instruments. In response, we report our results for PPP participation using OLS estimation for the sub-samples by bank size as a robustness check (Online appendix Table OA.4). We obtain positive and statistically significant coefficient estimates under OLS for all bank sizes.

Given our observed discrepancies in the impact of the PPP program by bank size, we also examine the overall effect on the program on SME lending by weighting our full sample by bank size, as proxied by total assets. Our results are shown in Column

[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, problem loans, and the share of tradable assets. 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 OA.6 and OA.7.

[22]Instrument diagnostic results are available on request from the authors.

5. The qualitative results are similar to our unweighted full sample. 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 a larger 7.4 percentage point increase in average annual small business and farm lending growth over our sample period.

In the appendix, we subject our base specification to a number of robustness checks. First (Table A1), we examine the implications of changes in specification, including dropping the conditioning variables, adding the instrumented PPPLF variable, using total capital ratio instead of our tier-1 risk adjusted measure, conditioning for lagged SME lending growth from 2018H1 through 2019H2, and using growth in the sum of conventional SME and PPP lending as the dependent variable. In all cases, our coefficient on PPP participation remains positive at statistically significant levels.[23]

We also examine the robustness of our results to changes in our sample (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 Dodd-Frank Act Stress Test (DFAST) and non-DFAST samples. This latter separation identifies those banks that are subject to regulatory stress testing, which differs modestly from our large bank sample.[24] The estimates coefficient on the PPP variable remains positive for all specifications.

Finally, Table A3 examines robustness to changes in estimation methods, including estimation by ordinary least squares, conventional standard errors, White's heteroscedasticity 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.

[23]We also estimate the determinants of above median level PPP participation in the final column of Table A1. We obtain significantly negative coefficients on the small and medium bank dummies, as well as $SME19H2$, suggesting that large banks and less SME-exposed banks had higher levels of PPP participation on average.

[24]The banks included in the DFAST sub-sample are listed in the online appendix, Table OA.3.

V.2. **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. 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 2.6 percentage point increase in average annual small business and farm lending growth over our sample period.[25]

For the conditioning variables, we again obtain positive and significant coefficient estimates for $LIQUID$ and $TIER1CAP$ for our full sample, 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 $SME19H2$ and $TRADABLE$, indicating again less SME lending growth on average for banks with greater greater existing exposure to SME lending and higher shares of tradable assets.

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 10% confidence level. $DEPOSITS$ enters positively at a 1% confidence level. The $COMMIT$ variable is 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 online appendix Table OA.9.[26]

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 as those reported in the base specifications.[27]

[25]First stage regression results for the PPPLF specifications are also available in the online appendix (Table OA.8).

[26]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 online appendix Tables OA.12 and OA.13. 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.

[27]These robustness tests are available in online appendix Tables OA.9, OA.10, and OA.11.

TABLE 4. PPPLF and Small Business and Farm Lending

	Full	Small	Medium	Large	WLS
PPPLF	0.335***	0.328***	0.347	-0.320	-0.589***
	(0.000590)	(0.103)	(0.675)	(1.574)	(0.0443)
LIQUID	0.112***	0.0953***	-0.565	1.108**	1.245***
	(0.00269)	(0.0349)	(0.371)	(0.500)	(0.159)
COMMIT	-0.0426*	-0.0146	-1.129***	-0.176	-0.637***
	(0.0230)	(0.0704)	(0.421)	(0.761)	(0.241)
DEPOSITS	0.0507***	0.0704	-0.225	0.254	-0.423***
	(0.0143)	(0.0439)	(0.340)	(0.549)	(0.0720)
TIER1CAP	0.129***	0.149***	-0.976***	-1.475	-1.047***
	(0.0137)	(0.0499)	(0.349)	(2.251)	(0.0890)
SME19H2	-0.194***	-0.195***	-0.501	0.532	-0.277***
	(0.000268)	(0.0223)	(0.434)	(0.455)	(0.0372)
PROB	-0.0342**	-0.0292	-1.207	8.557**	-0.0275
	(0.0168)	(0.122)	(1.187)	(4.006)	(1.234)
TRADEABLE	-0.0357***	-0.0424**	0.201	0.668*	0.274***
	(0.00351)	(0.0190)	(0.141)	(0.372)	(0.00391)
SMALLBANK	-0.00637***				0.0966***
	(0.0000577)				(0.0156)
MIDBANK	-0.0335***				0.0847***
	(0.000319)				(0.0189)
CONSTANT	0.0331**	0.00874	0.462	-0.293	0.430***
	(0.0146)	(0.0405)	(0.327)	(0.317)	(0.128)
N	3960	3852	83	25	3960

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; $TRADABLE$ is the share of tradable assets; and $SMALLBANK$ and $MIDBANK$ are indicator variables for small and medium-sized banks, respectively. See text for instruments used for $PPPLF$. Columns 2, 3, and 4 represent the sample of small, medium, and large banks respectively. Standard errors in parentheses are clustered by bank size. Column 4 estimated by weighted least squares, with observations weighted by total assets. Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

The remainder of the table repeats our base specification for sub-samples of small, medium and large banks (Columns 2, 3, and 4 respectively), and weighted by total assets (Column 5). Our coefficient estimate for $PPPLF$ is statistically significant and positive for our small bank sub-sample, but insignificant for the medium and large bank sub-samples. This discrepancy is likely driven by the weaker dependence of medium and large banks on the PPPLF as a tool for liquidity enhancement while participating in the PPP program. Similarly, we obtain a negative and statistically significant coefficient estimate for $PPPLF$ after weighting our observations by total assets (column 5). This again indicates the greater importance of the PPPLF program for the liquidity positions of small-sized banks.[28]

VI. Late-sample effects of PPP and PPPLF lending

As shown in Figure 1, 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. This period was also associated with a sharp decline in PPP exposure, which was close to zero by the end of our sample in 2024H2. 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 2.5 years of our sample, i.e. the period between 2022H1 and 2024H2. By this time, PPP loans outstanding had fallen close to zero, as most PPP debt had been either forgiven or repaid.[29]

Our dependent variable for this period is $\%\Delta SME22$, which measures average annualized growth in SME lending between 2022H1 and 2024H2. Our variables of interest are the same, PPP and $PPPLF$, measured as of the peak of both programs

[28]We obtain similar weak instrument diagnostic results for our bank size sub-samples for PPPLF participation as we did for the PPP. Our instrumented $PPPLF$ variable passes weak instrument tests for our full sample, with a Cragg-Donald statistic of 51.30 and an Anderson LM statistic of 195.75, which rejects under-identification at 5% and 1% confidence levels respectively. We also obtain a CLR statistic of 9.71 and an AR statistic of 18.93, both of which reject weak instruments at a 1% confidence level. These results are also available on request. However we again fail to reject weak instruments for our medium and large-bank sub-samples. In response, we also report our results for PPPLF participation under OLS estimation. Our OLS results are again consistent with our IV results. $PPLF$ enters positively and significantly in full and small bank samples, but insignficantly and significantly negative for our medium and large bank sub-samples respectively. Our full sample results are reported in online appendix Table OA.11, and our sub-sample OLS results are available on request.

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

TABLE 5. PPP and Small Business and Farm Lending 2022H1 to 2024H2

	Full	Small	Medium	Large	WLS
PPP	-0.274***	-0.261**	-13.41	-0.867	0.869**
	(0.0247)	(0.129)	(25.21)	(2.156)	(0.409)
LIQUID22	0.0465***	0.0479*	-0.686	0.115	0.0354
	(0.00236)	(0.0249)	(1.367)	(0.222)	(0.0428)
COMMIT2	0.105***	0.114	0.730	-0.0634	-0.327***
	(0.00818)	(0.100)	(2.859)	(0.628)	(0.108)
DEPOSITS22	-0.0423***	-0.0306	-0.231	-0.607	-0.615***
	(0.00980)	(0.0437)	(0.736)	(0.410)	(0.0376)
TIER1CAP22	-0.0473***	-0.0455*	-1.286	-1.585	-0.167
	(0.00115)	(0.0235)	(1.552)	(1.218)	(0.182)
SME22H1	0.0497***	0.0473**	7.916	0.963***	0.139***
	(0.00140)	(0.0231)	(14.91)	(0.371)	(0.0198)
PROB22	-0.0163	-0.0203	-2.174	8.388*	1.707
	(0.0206)	(0.179)	(3.004)	(4.528)	(1.096)
TRADEABLE22	0.0211***	0.0204	0.746	0.729*	0.0281
	(0.00115)	(0.0143)	(1.036)	(0.388)	(0.0212)
SMALLBANK	0.0673***				-0.0396***
	(0.000459)				(0.00330)
MIDBANK	0.0178***				-0.0615***
	(0.000461)				(0.00457)
CONSTANT	0.0158	0.0722**	0.551	0.425	0.543***
	(0.00975)	(0.0367)	(0.395)	(0.311)	(0.0884)
N	3960	3852	83	25	3960

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, 3, and 4 represent the sample of small, medium, and large banks respectively. Column 5 includes weighted least squares specifications. Standard errors in parentheses are clustered by bank size. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

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. Our full sample results are shown in Column 1. PPP enters significantly negative at a 1% confidence level. The point estimate for this variable indicates that a 1 standard deviation increase in PPP was associated with an annualized decrease in growth of 1.2 percentage points over the last two years of our sample period.[30]

However, our results for the samples split by size as well as weighted by total bank assets reveals a systematic disparity in the degree to which banks reduced the outsized SME lending exposure they built up over the early portion of our sample period. Columns 2, 3, and 4 again report our results for PPP participation for small, medium, and large bank sub-samples respectively. Of the three sub-samples, only the small bank sub-sample indicates a significantly negative late-sample response for PPP participation in SME lending. Our point estimate for that sub-sample indicates that a one standard deviation increase in PPP participation is associated with a reduction in late-sample SME lending growth on average of 1.15 percentage points. In contrast, the coefficient estimates for the medium and large bank sub-samples are insignificant. Indeed, we also obtain a positive and statistically significant at a 10% confidence level coefficient estimate for the late-sample SME lending response to heightened PPP participation.

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 positively, with the exception of the medium-sized bank sub-sample, which is also positive, but statistically insignificant. These results suggest that banks were not drawing down on SME exposure *per se*. Instead, the negative coefficient estimate

[30]In online appendix Table OA.14, we examine the implications of 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. The results are robust to either of these alternative specifications. Our results are also robust to conditioning for growth in SME lending prior to the onset of our late sample for our PPPLF participation results below, reported in online appendix tables OA.16 and OA.17.

we obtain for small banks and our overall full sample suggest that the incentives associated with the PPP program induced some banks. particularly smaller banks, to take on a greater share of SME lending than desired in their steady state lending portfolio.[31]

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 2024H2, while all of our conditioning variables measure bank characteristics going into this latter sample portion at 2022H1.

Our $PPPLF$ variable also enters significantly negatively at a 1% confidence level for our full sample for the late-sample period (Column 1). Our point estimate indicates that a one standard deviation increase in PPPLF participation was associated on average in a 2.0 percentage point reduction in annualized SME lending growth over the latter two years of our sample on average.

Again though, we observe notable heterogeneity by bank size. Our small bank sub-sample enters significantly negatively at a 10% confidence level, but our coefficient estimates for both medium and large-sized banks are statistically insignificant. Still, as these sub-samples also enter with a negative point estimate, our weighted least squares specification (Column 5) shows $PPPLF$ also entering significantly negative at a 1% confidence level for all banks on average when weighted by bank size.[32]

We interpret our late sample negative coefficient estimates on the PPP and $PPPLF$ variables as indicating that small banks considered their elevated SME exposures associated with the PPP and PPPLF programs excessive at the point of the termination of those programs. They therefore moved over the final year of our sample to re-balance that exposure away from SME lending. However, this rebalancing fell short of the initial increases in SME lending associated with the programs, leaving overall program-related exposure elevated at the end of our sample. Moreover, this was not the case for medium and large banks, who did not demonstrate any statistically significant responses to elevated exposures over the latter portion of our sample.

[31]Again, the medium-sized bank sub-sample is an exception as $SME22H1$ enters insignificantly.

[32]NOTE ON NEW TABLES OA.16 and OA.17

TABLE 6. PPPLF and Small Business and Farm Lending 2022H1 to 2024H2

	Full	Small	Medium	Large	WLS
PPPLF	-0.260***	-0.250**	-0.393	-5.117	-1.594***
	(0.0195)	(0.111)	(0.586)	(5.344)	(0.0803)
LIQUID22	0.0290***	0.0306	-0.112	0.231	0.101
	(0.00356)	(0.0249)	(0.251)	(0.389)	(0.113)
COMMIT22	0.0278**	0.0365	-0.580	0.371	0.209
	(0.0114)	(0.0715)	(0.403)	(1.109)	(0.298)
DEPOSITS22	-0.0812***	-0.0664	-0.611	-1.607**	-1.212***
	(0.0148)	(0.0434)	(0.443)	(0.781)	(0.0138)
TIER1CAP22	-0.0477***	-0.0456*	-0.655	-0.475	-0.274
	(0.00155)	(0.0237)	(0.436)	(1.181)	(0.202)
SME22H1	0.0312***	0.0303	-0.410	0.514	-0.00651
	(0.00104)	(0.0250)	(0.592)	(0.696)	(0.127)
PROB22	0.117***	0.0991	-0.515	6.278	1.427***
	(0.00295)	(0.176)	(1.764)	(4.935)	(0.248)
TRADEABLE22	0.0139***	0.0131	0.209	0.642*	0.234***
	(0.000870)	(0.0154)	(0.189)	(0.384)	(0.0133)
SMALLBANK	0.0604***				0.0785***
	(0.000242)				(0.0213)
MIDBANK	0.0152***				0.0256
	(0.000336)				(0.0170)
CONSTANT	0.0565***	0.103***	0.645*	1.137*	1.004***
	(0.0140)	(0.0382)	(0.372)	(0.676)	(0.0639)
N	3960	3852	83	25	3960

Note: IV estimation with dependent variable $\%\Delta SME22$, average annualized growth in small business and farm lending between 2022H1 and 2024H2. $PPPLF$ 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; $TRADABLE$ is the share of tradable assets in a bank's portfolio, and $SMALLBANK$ and $MIDBANK$ are indicator variables for small and medium-sized banks, respectively. All columns are instrumental variable regressions. Columns 2, 3, and 4 represent the sample of small, medium, and large banks respectively. Column 5 includes weighted least squares specifications. Standard errors in parentheses are clustered by bank size. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

VII. Conclusion

This paper examines growth in SME lending by U.S. commercial banks from the beginning of the pandemic period through the end of 2024, a time by which bank exposure to PPP loans were essentially eliminated. We find persistent and economically important increases in conventional 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 2.0 and 2.6 percentage points respectively. This results in large cumulative increases in SME lending that appear to outlast the programs.

Our findings for the PPP program are driven by the small and large banks in our sample, as both showed statistically significant positive dependence on instrumented PPP participation, while the impact of the PPP program on persistent medium-sized bank lending was insignificant. In contrast, the long-term impact of the PPPLF program was concentrated among small banks, the primary targets of the program, while the impacts on both medium and large-sized banks were insignificant.

Our results also illustrate the importance of including small and medium-sized banks in assessing the impact of programs on SME lending. While available information on those banks' lending is more limited, a substantial share of SME lending comes from non-stress tested banks, 63% percent in our sample. We find that 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.

We characterize the impacts of these programs as persistent, rather than permanent, based on our findings for SME lending growth over the last two-and-a-half years of our sample. By this time, exposure to PPP funds had largely been exhausted. In aggregate, the data show that small banks moved to reduce the very elevated levels of SME lending that they had built up during the pandemic. Our results for this later period show that reductions in SME lending were associated with prior participation in both programs for banks on average, even after conditioning for initial SME lending levels.

Still, these reductions are sufficiently small that the increase in SME exposure has outlasted the PPP and PPPLF programs. 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 banks had developed relationships with their PPP borrowers following participation in the program.

Given that the government guarantees on PPP borrowing removed any incentives for costly information gathering on PPP loan borrowers, the source of these relationships are unclear. One possibility is that the simultaneous large increases in PPP and conventional SME lending at the outset of the pandemic played a role. It appears that PPP funds alone were insufficient for the borrowing needs of some SMEs during that period, and banks with greater PPP participation appear to have increased their conventional SME loan exposure 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 simultaneous conventional SME lending activity inspired by the PPP during the pandemic. Alternatively, however, the SME lending patterns we observed from the PPP and PPPLF program raise the possibility that the generation and servicing of even risk-free loans may yield inside information associated with lending relationships.

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TABLE A1. Changes in Specification

	Drop Covariates	PPP&PPPLF	Total Capital	Lag %ΔSME	%ΔSMEPPP	HighPPP
PPP	0.339***	2.137***	0.415***	0.476***	1.002***	
	(0.0113)	(0.706)	(0.00654)	(0.00970)	(0.0161)	
PPPLF		-1.301**				
		(0.522)				
SMALLBANK	-0.0313***	-0.0816***	-0.0143***	-0.0265***	-0.00858***	-0.0289***
	(0.000396)	(0.0305)	(0.000911)	(0.00158)	(0.000489)	(0.00224)
MIDBANK	-0.0406***	-0.0742***	-0.0389***	-0.0437***	-0.0301***	-0.0539***
	(0.000351)	(0.0160)	(0.000573)	(0.000570)	(0.000291)	(0.00140)
LIQUID		-0.00914	0.130***	0.0834***	-0.147***	0.103***
		(0.0512)	(0.0000336)	(0.00495)	(0.00723)	(0.00424)
COMMIT		-0.829***	-0.247***	-0.229***	-0.281***	-0.192***
		(0.272)	(0.00697)	(0.0118)	(0.00884)	(0.0115)
DEPOSITS		-0.152***	-0.0235	-0.000192	-0.124***	0.00477
		(0.0353)	(0.0169)	(0.0166)	(0.0114)	(0.0142)
TIER1CAP		0.0951***		0.0923***	0.0302***	0.153***
		(0.0147)		(0.0164)	(0.00826)	(0.0176)
SME19H2		-0.330***	-0.233***	-0.211***	0.110***	-0.212***
		(0.0366)	(0.000344)	(0.00137)	(0.00349)	(0.00242)
PROB		0.554***	0.113***	0.0660***	-0.302***	0.128***
		(0.163)	(0.0126)	(0.00904)	(0.0379)	(0.0127)
TRADEABLE		-0.0606***	-0.0205***	-0.0330***	0.0238***	-0.0479***
		(0.0122)	(0.00118)	(0.00347)	(0.000198)	(0.00282)
TOTCAP			0.0517**			
			(0.0243)			
%ΔSME18				0.00770***		
				(0.0000398)		
HIGHPPP						0.0475***
						(0.00214)
CONSTANT	0.0808***	0.270***	0.113***	0.0931***	0.0960***	0.0801***
	(0.000179)	(0.0533)	(0.0166)	(0.0154)	(0.0105)	(0.0141)
N	3960	3960	3960	3915	3991	3960

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 %ΔSME with %Δ$SMEPPP$, average annualized growth in the sum of SME lending and PPP lending between 2019H2 and 2024H2. Column 5 replaces dependent variable %ΔSME with %Δ$SMELT$, cumulative growth in SME lending between 2019H2 and 2024H2. Column 6 dependent variable is $HIGHPPP$, which equals 1 if a bank's PPP value is greater than the median value and 0 otherwise. Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

TABLE A2. Changes in Sample

	Truncate	Win 1-99	Win 5-95	DFAST	NONDFAST
PPP	0.376***	0.556***	0.429***	9.063***	0.462***
	(0.0195)	(0.00941)	(0.0105)	(3.363)	(0.132)
LIQUID	0.0372***	0.148***	0.0631***	1.632***	0.0679**
	(0.00335)	(0.00441)	(0.00397)	(0.363)	(0.0297)
COMMIT	-0.114***	-0.326***	-0.191***	-0.722	-0.221**
	(0.00473)	(0.0193)	(0.00791)	(0.658)	(0.0957)
DEPOSITS	0.00378*	0.00975	0.000102	-1.169*	0.0277
	(0.00199)	(0.0317)	(0.0109)	(0.697)	(0.0362)
TIER1CAP	0.0694***	0.227***	0.0752***	1.696*	0.144***
	(0.00638)	(0.0185)	(0.0141)	(0.972)	(0.0339)
SME19H2	-0.134***	-0.333***	-0.179***	-0.326	-0.220***
	(0.000742)	(0.00132)	(0.000861)	(0.614)	(0.0181)
PROB	0.0387***	0.156***	0.129***	9.412***	0.0773
	(0.00446)	(0.0195)	(0.00398)	(3.419)	(0.116)
TRADEABLE	-0.0180***	-0.0613***	-0.0265***	1.049***	-0.0467***
	(0.00151)	(0.00368)	(0.00291)	(0.383)	(0.0159)
SMALLBANK	0.00773***	-0.121***	-0.00599***		
	(0.00177)	(0.000916)	(0.00138)		
MIDBANK	-0.00518***	-0.140***	-0.0236***		
	(0.00120)	(0.000657)	(0.000634)		
CONSTANT	0.0447***	0.188***	0.0677***	0.195	0.0419
	(0.00137)	(0.0285)	(0.0104)	(0.449)	(0.0314)
N	3787	3960	3960	30	3930

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. Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

TABLE A3. Changes in Estimation

	OLS	PPP&PPPLF	Std. SE	Robust SE	Region Cluster	TOBIT	WLS SME Share
PPP	0.829**	2.137***	0.457***	0.457***	0.457***	0.829***	0.802***
	(0.0130)	(0.706)	(0.132)	(0.140)	(0.0860)	(0.175)	(0.0704)
LIQUID	0.0803**	-0.00914	0.0863***	0.0863**	0.0863**	0.0804*	0.0757*
	(0.00486)	(0.0512)	(0.0295)	(0.0362)	(0.0374)	(0.0469)	(0.0402)
COMMIT	-0.427**	-0.829***	-0.215**	-0.215**	-0.215**	-0.427***	-0.374***
	(0.0222)	(0.272)	(0.0968)	(0.103)	(0.106)	(0.0644)	(0.0538)
DEPOSITS	-0.0168	-0.152***	0.00876	0.00876	0.00876	-0.0168	-0.117***
	(0.0211)	(0.0353)	(0.0363)	(0.0420)	(0.0342)	(0.0465)	(0.0435)
TIER1CAP	0.113*	0.0951***	0.123***	0.123**	0.123**	0.113*	-0.00736
	(0.0164)	(0.0147)	(0.0342)	(0.0481)	(0.0597)	(0.0599)	(0.118)
SME19H2	-0.217***	-0.330***	-0.222***	-0.222***	-0.222***	-0.217***	-0.111***
	(0.00273)	(0.0366)	(0.0184)	(0.0198)	(0.0103)	(0.00983)	(0.00967)
PROB	0.165**	0.554***	0.0907	0.0907	0.0907	0.165	0.313***
	(0.00508)	(0.163)	(0.116)	(0.124)	(0.147)	(0.137)	(0.0455)
TRADEABLE	-0.0176	-0.0606***	-0.0403**	-0.0403**	-0.0403*	-0.0176	-0.0227
	(0.00415)	(0.0122)	(0.0160)	(0.0182)	(0.0215)	(0.0282)	(0.0182)
SMALLBANK	-0.0488***	-0.0816***	-0.0233	-0.0233	-0.0233	-0.0488	-0.0464***
	(0.000596)	(0.0305)	(0.0246)	(0.0369)	(0.0426)	(0.0487)	(0.00711)
MIDBANK	-0.0604***	-0.0742***	-0.0428*	-0.0428	-0.0428	-0.0604*	-0.0491***
	(0.000375)	(0.0160)	(0.0258)	(0.0373)	(0.0262)	(0.0321)	(0.00377)
PPPLF		-1.301**					
		(0.522)					
CONSTANT	0.114	0.270***	0.0825**	0.0825	0.0825*	0.114*	0.178***
	(0.0195)	(0.0533)	(0.0373)	(0.0503)	(0.0501)	(0.0622)	(0.0503)
N	4178	4178	3960	3960	3960	4177	3960

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 reports WLS with weights by SME share. Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$