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Who Supplies PPP Loans (and Does It Matter)? Banks, Relationships, and the COVID Crisis

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Abstract

We analyze the bank supply of credit under the Paycheck Protection Program (PPP). The literature emphasizes relationships as a means to improve lender information, which helps banks manage credit risk. Despite imposing no risk, however, the PPP supply reflects traditional measures of relationship lending: decreasing in bank size and increasing in prior experience, commitment lending, and core deposits. Our results suggest a new benefit of bank relationships: They help firms access government-subsidized lending. Consistent with this benefit, we show that the bank PPP supply, based on the structure of the local banking sector, alleviates increases in unemployment.

I. Introduction

When governments intervene in the financial system and the economy, they often do so by influencing or bailing out banks. For example, in 1998, the Federal Reserve effected a private-sector bailout of the hedge fund Long-Term Capital Management through moral suasion of their main counterparties, banks. In 2008, the housing sector, which lay at the center of the crisis, did not receive a substantial bailout. Instead, banks (the primary provider of mortgage credit) were the focus of policy interventions with the Troubled Asset Relief Program and the first round of quantitative easing, as well as the Home Affordable Modification Program (HAMP) and the Home Affordable Refinance Program (HARP).[1] In 2020, the Federal Reserve created the Main Street Lending program to help middle-market firms gain access to credit, but it did so by providing liquidity support to banks, not

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[1]For a critique of these actions, see Mian and Sufi (2014).

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to firms directly. Also in 2020, the Federal Reserve created the Money Market Mutual Fund Liquidity Facility (MMLF), in which it uses banks to provide liquidity support to money funds. This article uses microeconomic evidence from the Paycheck Protection Program (PPP) to provide further evidence that banks act as the main conduit for access to government subsidies.[2] We argue that our results provide a new (or perhaps unrecognized) rationale for the benefit to firms of close banking relationships.

We quantify the importance of banks in general, and relationship banks in particular, in supplying subsidized credit under the PPP program, created as part of the Coronavirus Aid, Relief, and Economic Security (CARES) Act.[3] The PPP aims to help small businesses avoid laying off their workers during the peak of the COVID-19 economic crisis. We show that relationship banks supply more of this credit to their borrowers and that localities with more relationship banking receive PPP credit earlier. As a result, these areas experience smaller increases in unemployment. Despite this intended effect of the PPP program, we find no evidence that broader measures of economic output (i.e., small business revenues or total spending) respond to the program.

We start by asking: Who supplies business credit during the COVID crisis? Aggregate figures provide a partial answer. As shown by Li, Strahan, and Zhang (2020), before the PPP program began in April, large banks responded to large firms' widespread demand for liquidity by expanding lending on an unprecedented scale during the last 3 weeks of the first quarter of 2020. During March, liquidity in money markets and bond markets became constrained, leading firms to "run" to their banks and draw funds from preexisting credit lines. This expansion in bank lending is evident in Figure 1, which compares cumulative loan growth for large versus small banks. After March, however, large banks experienced contractions in lending as some large borrowers, with renewed access to liquidity from the markets, paid back their loans.[4]

As shown in Figure 1, lending by small banks, which traditionally focus on relationship lending to small firms, grows sharply in April, reflecting their participation in the PPP program. Small and medium-sized banks (those with assets under \$50 billion) provide about two-thirds of the loans under the PPP program (\$310 billion out of \$494 billion by all banks, or 63%). This share exceeds their share of lending to small businesses before the COVID crisis, which was just 44% at the end of 2019.

In contrast to PPP loans, new lending to businesses outside the PPP program stagnated for all banks during the second quarter. Figure 2 shows that PPP lending intensity correlates strongly with small-bank profitability during 2020 (relative to 2019). The program contained both an implicit interest rate subsidy (a 1% interest rate, which exceeds the yields on risk-free Treasuries at the time) and an origination

[2]Lopez and Siegel (2021) study the role of the Federal Reserve's Paycheck Protection Program Liquidity Facility on bank lending to small business.

[3]We focus only on the PPP program during the peak of the COVID crisis in the spring and summer of 2020. Additional funds were disbursed to small business in 2021 under later rounds of the PPP program.

[4]For further evidence on the effects of bond market disruptions, see Acharya and Steffen (2020), Darmouni and Siani (2020), Chodorow-Reich, Darmouni, Luck, and Plosser (2020), Greenwald, Krainer, and Pascal (2020), and Hotchkiss, Nini, and Smith (2020).

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FIGURE 1

Cumulative Commercial and Industrial Lending Growth

Figure 1 plots the cumulative commercial and industrial loan growth since Jan. 2020 at large and small banks in the United States. The data come from the Federal Reserve's H.8 weekly statistical release. Large banks are the top 25 domestically chartered commercial banks by assets, and small banks include the rest of the banks.

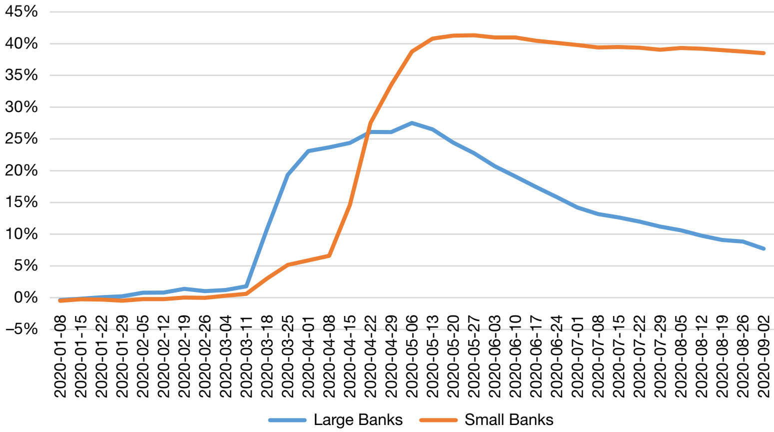
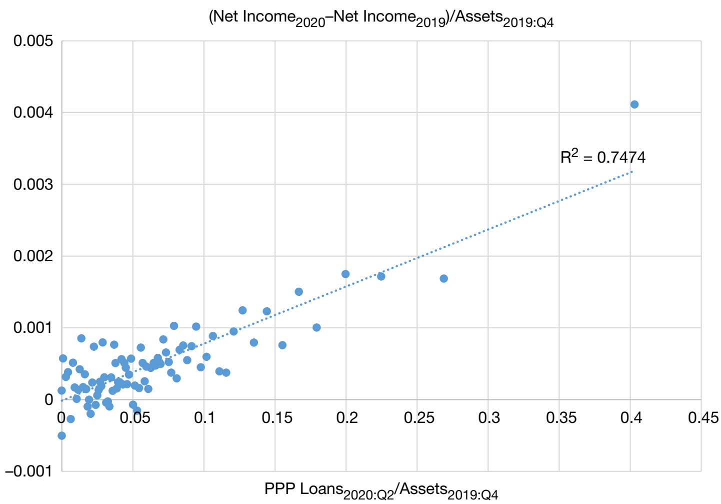


FIGURE 2

Change in Small-Bank Profitability and Intensity of PPP Lending

Figure 2 plots the change in small-bank profitability between 2019 and 2020 (change in net income scaled by 2019 assets) against the intensity of the bank's PPP lending (PPP loan amount as of 2020:Q2 scaled by 2019 assets). Small banks are divided into 100 bins based on their PPP lending intensity. The average PPP lending intensity and change in profitability are calculated for banks in each bin. Each dot on the scatter plot represents a bin of banks.



fee paid to banks of 3%–5% for most loans. The generosity of the program terms was likely more appealing to smaller banks, partly because small business lending constitutes a larger proportion of their business compared with larger banks, and partly because the large banks had been inundated with loan demand from their large customers during the last weeks of March.

Figure 3 reports state-level heat maps of the quantity of PPP credit in the first round (Apr. 3–17) and second round (Apr. 27–Aug. 9) of the program, along with a similar one for the state prevalence of small banks. These figures suggest visually, and we verify in our regressions formally, the importance of relationship-oriented banks in getting the PPP credit to their borrowers immediately. States with more small banks receive more PPP loans in the first round (correlation = 0.65), whereas this relationship reverses sign in the second round (correlation = –0.77).

Press accounts and anecdotal evidence suggest that firms with better access to banks before the COVID crisis were able to get PPP funding quickly at the outset of the program, which was overwhelmed with demand and had its first-round funds exhausted in just 2 weeks (Figure 4).[5] Pre-COVID relationships became valuable by allowing firms close to their banks to gain access to the government-subsidized lending, especially early in the implementation of the program. Because relationship banks have a long-term interest in the survival of their borrowers, they have an incentive to help those borrowers access the PPP program. Moreover, the rapid launch of the program created confusion for many potential applicants about things like the meaning of "loan forgiveness," as well as requirements surrounding what components of payroll were forgivable. Relationship banks likely were in the best position to help small businesses understand the terms of the program and help them apply successfully.

To test this idea comprehensively, we focus on how banks' characteristics explain their role in the PPP program. We estimate regressions based on quarterly Call Report data, which capture overall business lending as well as lending supplied by banks under the PPP program. We contrast lending patterns in March, which respond to the crisis in securities markets, with those in April and subsequent months, which respond to the economic downturn and the advent of government subsidies. Lending after March expands most at banks typically associated with close relationships with their borrowers. In particular, lending grows faster at small banks, at banks with high levels of small business loans prior to the crisis, at banks with high levels of unused business credit commitments before the crisis, and at banks raising more local retail deposits. And these effects are strongest for the smaller banks.

We then decompose business lending during 2020:Q2 into loans made under the PPP program versus all other business lending. Essentially all of the growth in lending during the second quarter comes under the PPP program, and all of the connections between relationship measures and lending growth reflect PPP lending (as opposed to other bank loans to businesses).

We validate the importance of relationships using two distinct empirical strategies. First, we separate each bank's PPP lending based on whether or not the borrower resides in one of the bank's core markets, defined as a county in which the bank owns at least one branch. As we show, the measures of relationships explain lending in core markets but only weakly in peripheral ones. We also show that the relationship variables matter most during the first round of PPP lending, consistent with the idea that banks advantaged their relationship borrowers over

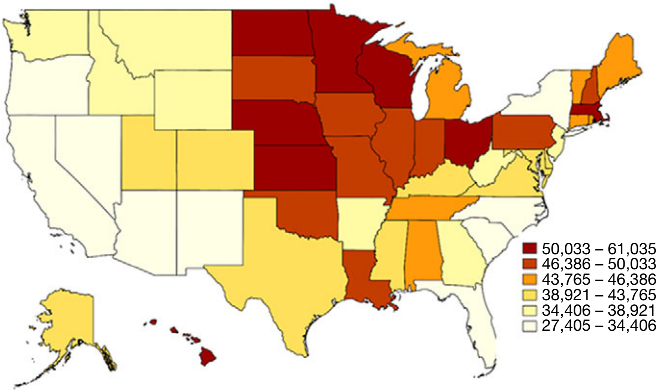
[5]See for example, "PPP Money Abounded—But Some Got It Faster Than Others," *Wall Street Journal*, Oct. 6, 2020.

FIGURE 3

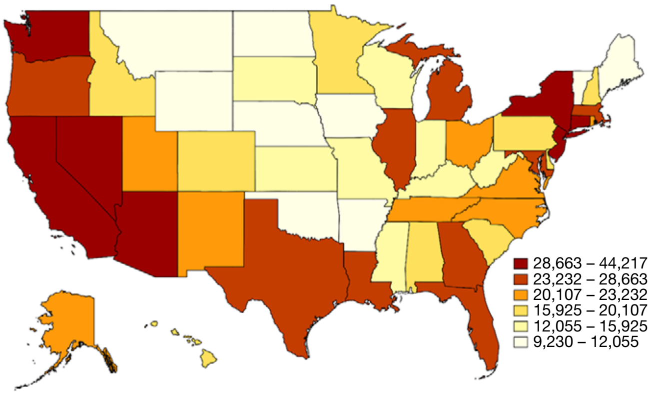
PPP Lending and Share of Small Bank Branches

Graph A of Figure 3 plots the heat map of state-level total PPP loan amount (in dollars) received during the first round of PPP (Apr. 3–16) scaled by the number of establishments with fewer than 500 employees in 2018. Graph B plots the heat map of state-level total PPP loan amount (in dollars) received during the second round of PPP (Apr. 27–Aug. 9) scaled by the number of establishments with fewer than 500 employees in 2018. Graph C plots the heat map of the share of bank branches owned by small banks (with less than $10 billion in assets) in 2019.

Graph A. PPP Loan Amount (Round 1) per Small Establishment by State



Graph B. PPP Loan Amount (Round 2) per Small Establishment by State



Graph C. Share of Small Bank Branches by State

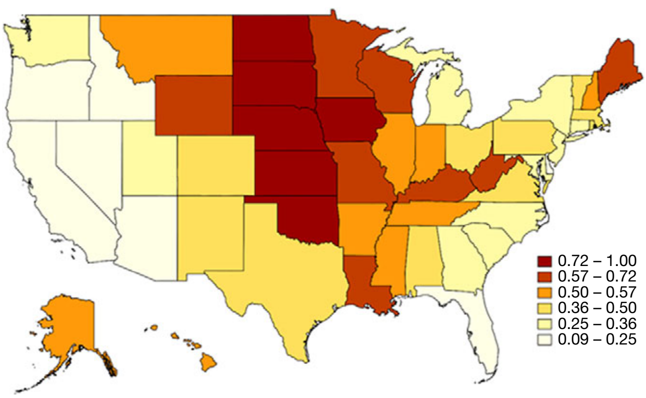
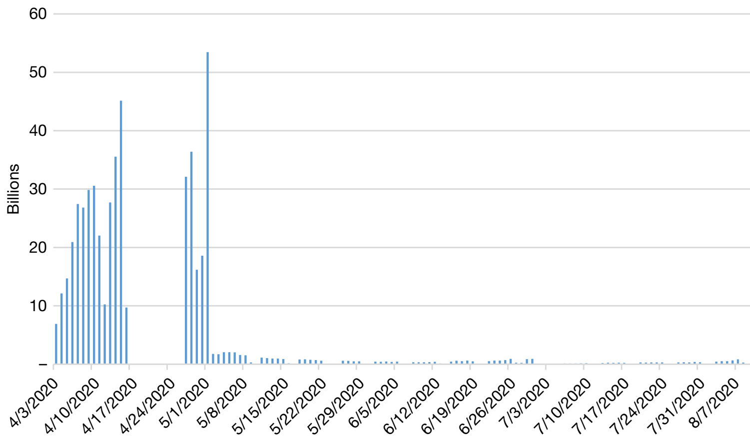


FIGURE 4

Daily Approved PPP Loan Amount

Figure 4 plots the daily approved Paycheck Protection Program (PPP) loan amount. The data come from the PPP loan-level data set of the Small Business Administration (SBA).



others by helping them access the PPP program first. Second, we report within-bank tests to compare lending as a function of bank branch and lending characteristics in banks' core markets. These tests show that banks lent more to PPP borrowers in their most important core markets (those where they made more small business loans prior to COVID). We also show that PPP lending increases with the average age of branches located in the core markets. The within-bank tests suggest that relationships from long-standing ties with the local economy affect PPP lending. That is, even after controlling for all cross-bank variation (with fixed effects), bank relationships still strongly predict banks' PPP credit supply.

In the last part of our analysis, we link PPP credit to local real outcomes. We show that variation in the quantity of PPP credit across counties reflects both the size and structure of local banks. Specifically, two pre-COVID measures of banking structure correlate strongly with the quantity of PPP credit across geographies after controlling for demographic and economic covariates. First, and most simply, areas with more branches per eligible establishment (before COVID) receive more PPP credit. Second, areas with more local relationship banks (based on our bank-level predictive model) also receive more PPP credit during the first round of allocations (the first 2 weeks of April). We use the relationship variable to capture local PPP credit-supply conditions. Unlike the overall size of the local banking system, this variable reflects credit supply, not demand, because it correlates negatively with PPP credit from external banks. We then tie the local PPP lending supply to real outcomes. Areas that receive more of the local PPP lending supply in the first round (because of the presence of relationship banks), we show, experience smaller increases in unemployment.

Several articles have assessed the impact of the PPP program on economic outcomes. For example, Granja, Makridis, Yannelis, and Zwick (2020) find that more PPP first-round funds flow into localities less affected by COVID and that the effects of the PPP program on employment are small relative to the scale of the funds allocated. Autor, Cho, Crane, Goldar, Lutz, Montes, Peterman, Ratner, Villar, and Yildirmaz (2020) find evidence that employment falls less at firms eligible for PPP loans than at otherwise-similar firms. Cherry, Jiang, Matvos, Piskorski, and Seru (2020) also find some evidence that PPP lending increases employment, but the effects are small relative to the cost of the program. Barraza, Rossi, and Yeager (2020) find that areas with more offices of banks that issued loans backed by the Small Business Administration (SBA) in 2019 experience smaller increases in unemployment after the initiation of the PPP program. Faulkender, Jackman, and Miran (2020) also find a beneficial effect of PPP lending on unemployment, but it is much larger than the effect found in these other studies. Using survey evidence from Oakland, Bartlett and Morse (2021) find that access to PPP credit improves firm survival probability.

Consistent with most of this literature, we also find benefit in a better PPP supply: It helps preserve local employment (although magnitudes are small). Because our variation only compares unemployment patterns between counties based on whether or not they receive PPP loans in the first round, our empirical strategy does not identify the overall impact of the program. Ultimately, most PPP applicants did receive funds; the program closed with over $100 billion in unallocated funds. As such, we hesitate to use our approach to assess the effectiveness of the program itself. Moreover, tests based on unemployment patterns or business survival may not capture the longer-run benefits of the program, such as maintaining connections between firms and employees and the nonpecuniary benefits associated with such connections (e.g., better mental health). Instead, we use this last test to provide further evidence of the benefits of relationship lending, even when the government has removed all risk from credit providers.

Ours is the first article to exploit Call Report data to study how bank relationship characteristics affect the overall supply of PPP loans; this approach allows us to compare patterns in PPP lending with those in nonsubsidized bank business lending. Several recent articles have argued that bank relationships have helped firms gain access to PPP loans. Amiram and Rabetti (2020) focus on publicly traded firms and find that firms with existing banking relationships receive larger PPP loans faster. Balyuk, Prabhala, and Puri (2020) study small public firms and find benefits associated with access to PPP credit. Cororaton and Rosen (2020) also study publicly traded firms and find that smaller public firms with more employees, fewer investment opportunities, and COVID-19 exposure are more likely to borrow from PPP funds. Erel and Liebersohn (2020) find that borrowers in areas with fewer bank branches, lower incomes, and more minority populations are more likely to access PPP funds via financial technology (fintech) firms rather than banks.[6] A number of studies show that small community banks provide an outsized share of PPP loans (Balyuk et al. (2020), Faulkender et al. (2020), and James, Lu, and Sun (2020)). Bartik, Cullen, Glaeser, Luca, Stanton, Sunderam (2020) use firm

[6]Despite the important role of fintech lenders in some areas with few traditional banks, banks were by far the dominant provider of these loans. For example, the share of fintech lenders in the PPP program was small in both the early and late rounds (SBA (2020)). However, Fuster et al. (2021) show that fintech lenders gained substantial market share in the mortgage lending business relative to banks during 2020.

survey evidence, finding that firms with strong bank relationships are more likely to receive PPP loans, whereas Joaquim and Netto (2020) provide a theoretical analysis of bank incentives to lend under the program.[7]

Our article contributes a new dimension to the literature on relationship banking. All of the extant banking literature emphasizes that relationships reduce information asymmetry about aspects of borrowers' ability or willingness to repay.[8] Banks, the story goes, learn about their customers' businesses over time, monitor their cash flows and financial health, and lend based on a deep understanding of the businesses and their future prospects. PPP loans, in contrast, have no credit-risk exposure for lending banks, yet relationships strongly predict PPP supply. Banks act as gatekeepers for the PPP program, shepherding small businesses through the application process. Banks prioritize their relationship borrowers over others because managing the application process is less costly for them and because they have an economic interest in the long-term survival of their borrowers.[9] Our results suggest that a close bank relationship can help firms gain access to the program and that such access has a real effect. Hence, our results point to a new benefit to firms of close relationships with banks: They help their close customers gain access to government subsidies. Thus, whereas existing articles document that relationships are valuable for conventional reasons (e.g., as shown by Bolton, Freixas, Gambacorta, and Mistrulli (2016), relationship banks are more willing to stay with their borrowers during bad times), ours documents a less conventional but important reason (i.e., relationship banks help their borrowers gain access to government subsidies).

II. Background: The Paycheck Protection Program

The negative economic impact of the coronavirus pandemic became increasingly evident in Mar. 2020 as the spread of COVID-19 accelerated across the United States and individual states started to implement various emergency measures, including "lockdowns." For the week ending on Mar. 28, initial claims for unemployment insurance (seasonally adjusted) reached a historical high of 6.9 million.

[7]For evidence on government-guaranteed lending outside the United States, see Core and De Marco (2020).

[8]There is a long literature on bank relationship lending, which we will not review here. However, Petersen and Rajan (1994) is the seminal empirical analysis on the subject; they emphasize the role of duration in relationship formation. Berger, Miller, Petersen, Rajan, and Stein (2005) and Degryse and Ongena (2005) provide evidence that distance between borrowers and banks provides another proxy for relationships, although Petersen and Rajan (2002) argue that technology has reduced the importance of physical proximity to banks. Most of the literature finds that relationships are beneficial to firms, but Berger, Bouwman, Norden, Roman, Udell, and Wang (2020) find that (non-PPP) lending based on relationships during the COVID crisis came with higher spreads than other loans. Bank size has also been associated with relationship lending, motivated by Stein (2002), who argues that large, complex organizations are less able to manage the soft information embedded in lending relationships. The advent of technology has potentially limited the importance of these dimensions, as discussed by Berger and Black (2019). For a meta-analysis of the effects of relationships on the terms of bank loans, see Kysucky and Norden (2016).

[9]Humphries, Neilson, and Ulyssea (2020) use survey data to show that the smallest businesses face an information disadvantage in accessing PPP funds.

In response to this sharp and deep economic shock, Congress quickly passed the CARES Act, which was signed into law on Mar. 27. The CARES Act provides a total of $2.2 trillion in economic assistance for individuals, health-care providers, businesses, and state and local governments. The PPP, established under the CARES Act, aims to help small businesses "maintain their payroll, hire back employees who may have been laid off, and cover applicable overhead." The PPP program began to disburse funds on Apr. 3. Strong initial demand exhausted the $350 billion allocated within 2 weeks. An additional $320 billion of funding was added to the PPP program by the Paycheck Protection Program and Health Care Enhancement Act on Apr. 24. The program closed to new loan applications on Aug. 8, 2020, having distributed $525 billion (SBA (2020)), although the majority of funds had been distributed by early May (see Figure 4).

The PPP program provides loans to small businesses that are fully forgivable under certain conditions. Because the program's main aim is to reduce job separation, borrowers must maintain their employee and compensation levels to be eligible for forgiveness.[10] Banks distributed most of the PPP loans. Initially, only existing SBA lenders or federally insured depository institutions, credit unions, and Farm Credit System institutions could make PPP loans. The set of PPP lenders gradually expanded to include more nonbank lenders as the SBA approved their applications to participate. As of Aug. 8, when the PPP loan application period ended, nonbank lenders accounted for only 8.3% of the PPP loan count and 3.6% of the PPP loan amount (SBA (2020)).[11]

With a few exceptions, only businesses with fewer than 500 employees may apply for PPP loans.[12] Potential borrowers submit applications directly to private PPP lenders, who review the application materials and fund the loans. All PPP loans have the same terms, with an interest rate of 1% and a maturity of 2 years for loans made before June 5 or 5 years for loans made on or after June 5. The SBA also pays lenders processing fees up to a limit for originating PPP loans. Once approved, the SBA guarantees repayment at no cost to the borrowers or lenders; this guarantee ultimately has the backing of the full faith and credit of the U.S. Treasury. Hence, PPP loans carry a 0% risk weight under regulatory capital rules. In addition, the federal banking regulators (the Office of the Comptroller of the Currency (OCC), the FDIC, and the Federal Reserve) issued a joint interim final rule on Apr. 13 that effectively neutralizes the regulatory capital effects of PPP loans that are pledged by banks to the Paycheck Protection Program Lending Facility (PPPLF). Thus, regulated banks may originate PPP loans without any credit risk or marginal capital requirement.

[10]PPP loan forgiveness occurs under the following conditions: i) at least 75% of the loan proceeds cover payroll costs and the rest covers other overhead such as mortgage interest, rents, and utilities; and ii) the borrowers maintain their employee and compensation levels. See https://home.treasury.gov/policy-issues/cares/assistance-for-small-businesses for details.

[11]Those nonbank PPP lenders include small business lending companies, fintechs, nonbank Community Development Financial Institution (CDFI) funds, and other nonbank lenders.

[12]For example, firms in the accommodation and food services industry (with NAIC codes beginning with 72) are eligible for PPP loans if they employ fewer than 500 employees per physical location.

III. Who Supplies PPP Loans?

A. Data

We construct data on lending at the bank level by combining information from the Call Reports with information on the PPP program provided publicly by the U.S. SBA. The Call Report data normally capture bank lending to businesses both on and off the balance sheet (commercial and industrial (C&I) loans and unused loan commitments to businesses). An additional field added to the 2020:Q2 Call Report also separates out lending under the PPP program. Thus, we can compare PPP lending with non-PPP C&I lending during 2020:Q2. These data capture all loans on bank balance sheets as of June 30, 2020.

The SBA data contain firm-level records of borrowing under the PPP program, with information on the location of the borrower, the size of the loan, and the name of the lender. We merge these data into the Call Report data using the name of the lender. This procedure allows us to match most of the banks exactly. Of the nonmatched banks, approximately 400 made no PPP loans based on the Call Report data, so we assign 0 PPP loans to these banks. Overall, we identify PPP lending for 4,333 out of 4,980 banks. Collectively, the matched banks cover 95% of the total PPP lending in the SBA database, so we are confident that our measures accurately represent the bulk of the program. Some of the residual PPP lending is made by banks that we could not match, and some is made by nonbank financial institutions such as credit unions and CDFIs.

In order to understand the role of bank relationships and the importance of local banks, we separate lending from the SBA data into loans made by banks with branches in the borrower's county (deemed "core markets") versus loans made by banks without local branches (deemed "peripheral markets"). To achieve this separation, we use the location of each bank's branches as of June 2019 from the Summary of Deposits data set.[13] Because the branch locations are set before the onset of COVID, we can safely assume that the definition of core versus peripheral markets is exogenous. Approximately 71% of the total lending made by the matched banks comes from core markets, and the other 29% is from peripheral markets. The mean size of loans is slightly larger in core markets ($112,145) compared with peripheral markets ($100,321).

Table 1 reports summary statistics for bank-level measures of C&I lending growth, total C&I credit growth (C&I_ORIGINATIONS = loans plus unused commitments), and PPP loans. Unlike C&I lending growth, total credit growth does not reflect variation in credit-line takedown (or repayments). We scale these and the other bank characteristics by total assets at the end of 2019. We also include bank characteristics as of 2019:Q4, which we use to explain the 2020 lending. Panel A reports lending growth during the first and second quarters of 2020, Panel B reports summary statistics for PPP lending by lender size, and Panel C reports the 2019 pre-COVID bank characteristics.[14]

[13]See https://www.fdic.gov/regulations/resources/call/sod.html.

[14]We relate lending in the first and second quarters of 2020 to 2019 bank covariates, but the sample changes slightly over the 2 periods. Table 1 reports the summary statistics for the Q2 sample, but the Q1 figures are nearly identical.

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TABLE 1

Summary Statistics for Bank Characteristics

Table 1 reports summary statistics for bank commercial and industrial (C&I) lending and PPP lending, along with other balance-sheet characteristics, from Call Reports. The changes in lending are normalized by 2019:Q4 assets. C&I_ORIGINATIONS equals the sum of C&I loans on balance sheet plus unused C&I commitments. Core markets are counties in which the bank owns at least one branch, and peripheral markets are the other counties. log(DEPOSIT_WEIGHTED_AVERAGE_BRANCH_AGE) is derived from the 2019 Summary of Deposits data. DEPOSIT_WEIGHTED_COVID_DEATH_RATE is derived from county-level COVID death rates, which tally the number of COVID deaths per 100,000 people, within a bank's branch network. All other variables come from the pre–COVID period (2019:Q4) Call Reports. All variables, except log(ASSETS), are winsorized at the 1st and 99th percentiles.

	N	Mean	Std. Dev.	P25	P50	P75
Panel A. 2020 Lending						
Q1						
Change C&I	5,031	0.002	0.012	−0.002	0.001	0.005
Change C&I_ORIGINATIONS	5,031	0.003	0.014	−0.002	0.001	0.006
Q2						
Change C&I	4,980	0.054	0.067	0.012	0.037	0.070
Change C&I_ORIGINATIONS	4,980	0.058	0.070	0.014	0.040	0.076
Change NON_PPP_C&I	4,980	−0.002	0.016	−0.009	−0.002	0.002
Change NON_PPP_C&I_ORIGINATIONS	4,980	0.002	0.019	−0.006	0.000	0.007
PPP/ASSETS	4,980	0.057	0.069	0.013	0.040	0.076
Banks Matched to SBL Data						
PPP/ASSETS, core markets	4,366	0.038	0.041	0.007	0.025	0.054
PPP/ASSETS, peripheral markets	4,366	0.034	0.063	0.003	0.013	0.033
Panel B. PPP/ASSETS, by Bank Size						
Large (> $50 billion)	43	0.021	0.023	0.002	0.014	0.034
Medium ($10–$50 billion)	90	0.055	0.050	0.025	0.055	0.072
Small (< $10 billion)	4,847	0.058	0.069	0.013	0.040	0.076
Panel C. Bank 2019 Characteristics (for the 2020:Q2 sample)						
COMMITMENTS	4,980	0.031	0.035	0.007	0.021	0.043
SBL	4,980	0.047	0.037	0.021	0.041	0.065
CORE_DEPOSITS	4,980	0.780	0.074	0.741	0.791	0.834
C&I	4,980	0.083	0.065	0.040	0.069	0.111
LIQUIDITY	4,980	0.295	0.157	0.178	0.256	0.381
CAPITAL	4,980	0.118	0.035	0.097	0.109	0.128
SIZE	4,980	12.565	1.468	11.614	12.377	13.260
AGE	4,980	3.990	0.676	3.612	4.152	4.511
DEPOSIT_WEIGHTED_COVID_DEATH_RATE	4,980	23.580	34.052	2.854	9.400	27.762

As shown in Table 1, during 2020:Q1, C&I lending grew rapidly at the largest banks, mainly from large increases in credit-line drawdowns during March (Li et al. (2020), Chodorow-Reich et al. (2020)). The average bank, however, experienced a much smaller increase in C&I lending (approximately 0.23–0.25 percentage points of assets). Business lending grew much more rapidly in Q2, but this was only from the effects of the PPP program. Average PPP lending was 5.7% of assets. In contrast, non-PPP C&I lending shrank by 0.2% of assets. When we separate lending into core versus peripheral markets, we see similar amounts of lending. The average bank lends 3.4% of assets to borrowers in its core markets while lending 3.1% to borrowers in peripheral markets. As we will see, however, the emphasis on PPP lending to core markets is substantially higher for banks with strong local relationships.[15] As shown in Panel B, PPP intensity per unit of assets is lower for the largest banks (mean = 2.1%) compared with medium-sized (mean = 5.5%) or small banks (mean = 5.8%).

[15]The sum of lending to core plus peripheral markets exceeds total PPP lending from the Call Report data because the former measures include lending through early Aug. 2020, whereas the Call Report figure only includes PPP lending through June 30.

In our second set of tests, we focus on county-level real outcomes. High-frequency data are available online at the Opportunity Insights Economic Tracker website (https://tracktherecovery.org); Cherry et al. (2020) describe the data in detail. We focus on two of these outcomes (total revenue among small firms and total spending), as well as monthly unemployment rates at the county level from the Bureau of Labor Statistics.[16] Total revenues for small firms come from Womply. The series represents the percentage change in net revenue, calculated each weekday as a 7-day moving average (seasonally adjusted), indexed to Jan. 4–31, 2020. Small firms are defined as those meeting the SBA's threshold.[17] Total spending at the county level comes from daily aggregation of consumer spending based on debit- and credit-card transactions from Affinity Solutions.[18]

Table 2 reports summary statistics for the real outcomes. Both small business revenue and spending grow during the first months of 2020, before the advent of the COVID crisis, and then fall sharply thereafter. The declines are sharpest in March and April, when most states initiated lockdowns. Cherry et al. (2020) emphasize that the drop in spending is initially high across the income distribution. After the passage of the CARES Act, however, spending increases sharply in low-income areas (although it is still below levels before COVID) but much less so in high-income areas. (Despite these spending patterns, unemployment has more adverse effects in low-income areas.) As is clear in Table 2, unemployment increases sharply in April, then declines over the subsequent months. By the end of our sample, however, unemployment still well exceeds its level at the beginning of 2020.

B. Business Lending During the COVID Crisis

Tables 3–7 report regressions to explain bank lending during the 2020 COVID crisis. We first report models of overall C&I lending; second, we subdivide the analysis into PPP versus non-PPP C&I lending; third, we compare PPP lending patterns by bank size; fourth, we further subdivide PPP lending by market type (core vs. peripheral); and fifth, we report regressions at the bank-county level.

1. The Cross Section of Bank Lending

Table 3 reports the first of these tests, comparing the cross section of bank C&I lending during the first and second quarters of 2020. As outcomes, we use the change in C&I lending on balance sheet and the change in C&I credit (i.e., the sum of lending on balance sheet plus unused business commitments), both scaled by 2019:Q4 assets.

We measure all bank characteristics from the 2019:Q4 Call Reports and June 2019 Summary of Deposits. As such, they are unaffected by the COVID crisis. We separate bank characteristics into 3 tiers. First, we consider measures that the prior literature has associated with bank-firm relationship lending: COMMITMENTS

[16]See https://www.bls.gov/lau/#tables.

[17]To be specific, according to Cherry et al. (2020), "For each series, we construct daily values in exactly the same way that we constructed the consumer spending series. We first take a 7-day moving average, then seasonally adjust by dividing each calendar date's 2020 value by its corresponding value from 2019. Finally, we index relative to pre-COVID-19 by dividing the series by its average value over January 4–31."

[18]Other parts of the CARES Act support the housing market, such as mortgage forbearance programs (Cherry et al. (2020)).

TABLE 2

Summary Statistics for Bank Characteristics

Table 2 reports summary statistics for the data used in the county-time panel regressions of real economic outcomes on measures of PPP credit. SMALL_BUSINESS_REVENUE and TOTAL_SPENDING come from https://tracktherecovery.org; see Cherry et al. (2020). UNEMPLOYMENT_RATE is from the Bureau of Labor Statistics. SMALL_BUSINESS_REVENUE represents the percentage change in net revenue, calculated each weekday as a 7-day moving average (seasonally adjusted), indexed to Jan. 4–31, 2020. TOTAL_SPENDING is the seasonally adjusted credit-/debit-card spending relative to Jan. 4–31, 2020. UNEMPLOYMENT_RATE is by calendar month.

		SMALL_BUSINESS_REVENUE		TOTAL_SPENDING		UNEMPLOYMENT_RATE	
Time Period	Description	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Jan. 1, 2020–Feb. 15, 2020	COVID affects Asia	0.028	0.162	0.002	0.078	4.635	1.975
Pre-COVID (Feb. 16, 2020–Mar. 10, 2020)	COVID affects Western Europe	0.054	0.192	0.007	0.105	4.356	1.895
Crisis (Mar. 11, 2020–Apr. 3, 2020)	Global pandemic declared; financial-market turmoil	−0.150	0.269	−0.155	0.163	4.811	2.048
April (Apr. 4, 2020–Apr. 30, 2020)	Beginning of Paycheck Protection Program (PPP)	−0.229	0.289	−0.241	0.130	12.450	5.238
May	Continuation of PPP	−0.061	0.304	−0.125	0.138	10.348	4.117
June	Continuation of PPP	−0.028	0.294	−0.066	0.137	8.455	3.312
July	Continuation of PPP	−0.061	0.304	−0.050	0.124	7.878	3.082
August	PPP closed to new applications on Aug. 8, 2020						

TABLE 3

Bank Business Lending in the First Two Quarters of 2020

Table 3 reports regressions of bank commercial and industrial (C&I) lending in the first 2 quarters of 2020 on pre-COVID balance-sheet characteristics from Call Reports. The changes in lending are normalized by 2019:Q4 assets. C&I credit equals the sum of C&I loans on balance sheet plus unused C&I commitments. log(DEPOSIT_WEIGHTED_AVERAGE_BRANCH_AGE) is derived from the 2019 Summary of Deposits data. DEPOSIT_WEIGHTED_COVID_DEATH_RATE is derived from county-level COVID death rates within a bank's branch network. All other variables come from the pre–COVID period (2019:Q4) Call Reports. Standard errors are clustered by bank headquarters state. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	2020:Q1		2020:Q2	
	Change C&I	Change C&I_ORIGINATIONS	Change C&I	Change C&I_ORIGINATIONS
	1	2	3	4
Relationship Measures				
COMMITMENTS	0.0600***	0.00572	0.423***	0.507***
	(7.120)	(0.452)	(7.217)	(7.956)
SBL	−0.0117	6.36e-05	0.131**	0.111*
	(1.019)	(0.00522)	(2.094)	(1.696)
CORE_DEPOSITS	0.00261	0.00390	0.0763***	0.0836***
	(1.172)	(1.521)	(4.310)	(4.628)
Other Balance-Sheet Ratios				
C&I	0.0179**	0.0230**	0.0505	0.0790*
	(2.149)	(2.389)	(1.116)	(1.684)
LIQUIDITY	−2.38e-05	−0.00141	−0.0315***	−0.0331***
	(0.0173)	(0.912)	(4.388)	(4.514)
CAPITAL	0.0256**	0.0296**	0.0470	0.0553
	(2.402)	(2.357)	(0.982)	(1.070)
Other Control Variables				
SIZE	0.000402**	0.000192	−0.00436***	−0.00409***
	(2.559)	(1.326)	(3.973)	(3.695)
AGE	−0.000371	−0.000612	−0.0317***	−0.0324***
	(1.112)	(1.281)	(10.06)	(10.20)
DEPOSIT_WEIGHTED_ COVID_DEATH_RATE	9.73e-05*	2.23e-05	3.51e-05	3.42e-05
	(1.684)	(0.462)	(1.002)	(0.987)
Constant	−0.00917***	−0.00567	0.154***	0.148***
	(2.865)	(1.460)	(7.298)	(6.900)
No. of obs.	5,031	5,031	4,980	4,980
R^2	0.074	0.020	0.235	0.264

(undrawn loan commitments to businesses/assets), SBL (C&I loans under $1 million/assets), and CORE_DEPOSITS (transaction deposits plus insured time deposits/assets). For example, Petersen and Rajan (1994) is the first study to document the importance of relationships for bank lending to small firms. Berger and Udell (1995) show, using similar data, that credit lines (which generate undrawn loan commitments to business) are more associated with close bank–borrower relationships than term lending. Norden and Weber (2010) find that credit-line usage helps banks forecast default. Berlin and Mester (1999) show that core deposits help foster relationship lending by allowing banks to cross-subsidize borrowers over the credit cycle.[19] Second, we include 3 additional measures of bank balance sheets: the ratio of total C&I lending to assets (C&I), cash plus securities to assets (LIQUIDITY), and tier 1 leverage ratio (CAPITAL). C&I captures variation in banks' overall emphasis on lending to businesses, whereas the other 2 measures capture variation in the financial strength of the banks. Third, we include

[19]The theoretical idea that bank deposits provide information to lenders goes back further, to Fama (1985). For more recent empirical evidence, see Yang (2021).

2 additional bank characteristics: SIZE (the log of total assets) and AGE (the log of the deposit-weighted average age of the bank's branches). Panel C of Table 1 provides summary statistics for these explanatory variables. The deposit-weighted COVID death rate within a bank's branch network is derived from county-level COVID death rates obtained from the Opportunity Insights Economic Tracker website. All variables, except SIZE, are winsorized at the 1st and 99th percentiles.

Table 3 shows sharp differences in lending patterns between the first and second quarters of 2020, particularly for the effect of the 3 relationship characteristics. In Q1, COMMITMENTS strongly correlates with the change in C&I (column 1). As Li et al. (2020) show, the largest banks drive this result; these banks face unexpected increases in credit-line takedowns from their large borrowers who lose access to short-term funding markets and the bond market. Credit-line takedowns have no effect on the change in total credit originations (C&I_ORIGINATIONS = C&I loans plus unused business-loan commitments), however, which explains why COMMITMENTS has no significance in column 2. In Q2, the effect of COMMITMENTS increases relative to Q1 (by a factor of 8). In contrast to Q1, both SBL and CORE_DEPOSITS affect lending strongly in Q2. We know that these effects represent new credit originations, rather than credit-line takedowns, because both C&I lending growth and C&I credit growth respond similarly. Economic magnitudes are substantial. A 1-standard-deviation increase raises C&I lending by 1.7% of assets (COMMITMENTS), 0.6% of assets (CORE_DEPOSITS), and 0.5% of assets (SBL). For comparison, C&I lending grew by 5.4% of assets on average during the period. Beyond the relationship variables, we also find that banks with higher LIQUID_ASSETS increased lending less than other banks in Q2, as did larger banks and older banks.

Table 4 focuses on the difference between PPP lending patterns and those of other unsubsidized C&I lending (for 2020:Q2 only). PPP lending, as this comparison shows, drives the sharp differences in lending patterns between the first and second quarters. As in Q1, most of the correlations between bank characteristics and non-PPP C&I lending are weak. The exception is COMMITMENTS, which has a negative impact on non-PPP C&I lending (but no effect on non-PPP total credit). This reflects firms that had drawn funds during the March financial-market meltdown repaying those funds as bond-market access came back online (see Chodorow-Reich et al. (2020), Darmouni and Siani (2020)).

In Q2, the 3 relationship measures have very strong power to explain PPP lending (and the sign of the coefficient on COMMITMENTS becomes positive). This is interesting because PPP loans do not expose banks to credit risk. The U.S. government bears the downside risk. As such, this finding points to a benefit of banking relationships not emphasized before in the existing literature: Firms with strong bank relationships receive better access to the PPP credit, probably because many banks have limited capacity to help firms manage the application process, and this limited capacity is deployed first in the service of the bank's relationship borrowers.[20]

[20]According to press accounts about the PPP, "the program's expenses were also high, the big banks said. Bank of America devoted 10,000 employees to making loans at the program's peak, Mr. Moynihan said in July, and expects the next stage of the program—helping companies through the paperwork to

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TABLE 4

Bank Lending in the Second Quarter of 2020: PPP Versus Non-PPP C&I Lending

Table 4 reports regressions comparing bank non–Paycheck Protection Program (PPP) commercial and industrial (C&I) lending versus PPP lending in the second quarter of 2020 on pre-COVID balance-sheet characteristics from Call Reports. The changes in lending are normalized by 2019:Q4 assets. C&I credit equals the sum of C&I loans on balance sheet plus unused C&I commitments. log(DEPOSIT_WEIGHTED_AVERAGE_BRANCH_AGE) is derived from the 2019 Summary of Deposits data. DEPOSIT_WEIGHTED_COVID_DEATH_RATE is derived from county-level COVID death rates within a bank's branch network. All other variables come from the pre–COVID period (2019:Q4) Call Reports. Standard errors are clustered by bank headquarters state. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Change NON_PPP_C&I	Change NON_PPP_C&I_ORIGINATIONS	PPP
	1	2	3
Relationship Measures_IN_COUNTY			
COMMITMENTS	−0.0778***	0.000111	0.494***
	(8.225)	(0.00721)	(7.912)
SBL	0.00303	−0.0140	0.127**
	(0.219)	(1.024)	(2.168)
CORE_DEPOSITS	−0.00412	0.00148	0.0809***
	(1.502)	(0.526)	(4.514)
Other Balance-Sheet Ratios			
C&I	−0.0229***	0.00507	0.0716
	(3.616)	(0.700)	(1.573)
LIQUIDITY	−0.000192	−0.00117	−0.0320***
	(0.132)	(0.936)	(4.146)
CAPITAL	0.00222	0.00878	0.0427
	(0.375)	(1.016)	(0.897)
Other Control Variables			
SIZE	−0.00108***	−0.000728***	−0.00309***
	(5.601)	(3.516)	(2.685)
AGE	−0.000574*	−0.00128***	−0.0307***
	(1.851)	(3.136)	(9.094)
DEPOSIT_WEIGHTED_COVID_DEATH_RATE	8.33e-06	6.15e-06	2.36e-05
	(1.594)	(1.006)	(0.659)
Constant	0.0188***	0.0125***	0.132***
	(4.736)	(2.699)	(5.782)
No. of obs.	4,980	4,980	4,980
R^2	0.123	0.006	0.262

Table 5 reports estimates of these models separately for small (< $10 billion in assets), medium-sized ($10 to $50 billion in assets), and large (> $50 billion in assets) banks. This split further supports the relationship-banking interpretation. First, the largest banks, which focus much less on small relationship borrowers, lend much less in the PPP program per unit of assets than other banks (recall Panel C of Table 1). Second, the large banks exhibit little effect of the 3 relationship measures on PPP lending. COMMITMENTS and SBL are both insignificant in the regression. In contrast, both COMMITMENTS and SBL are very strongly tied to PPP lending for medium-sized and small banks. CORE_DEPOSITS only exhibits a strong connection to PPP for the small banks. On balance, relationships matter for both medium-sized and small banks but not for the large ones.[21]

have their loans forgiven, if they qualify—to be complicated and time consuming." See *New York Times*, "Despite Billions in Fees, Banks Predict Meager Profits on P.P.P. Loans," Oct. 1, 2020.

[21]The coefficients on the relationship variables differ statistically between the samples of large and small banks and between the samples of large and medium-sized banks (χ^2 ranging between 3.1 and 26.8), with the exception of CORE_DEPOSITS between the samples of large and medium-sized banks.

TABLE 5

Bank PPP Lending by Size

Table 5 reports regressions of bank Paycheck Protection Program (PPP) lending, normalized by 2019:Q4 assets, in the second quarter of 2020 on pre-COVID balance-sheet characteristics, from Call Reports. Large, medium-sized, and small banks are those with >$50 billion, $10–$50 billion, and <$10 billion in assets, respectively. log(DEPOSIT_WEIGHTED_AVERAGE_BRANCH_AGE) is derived from the 2019 Summary of Deposits data. DEPOSIT_WEIGHTED_COVID_DEATH_RATE is derived from county-level COVID death rates within a bank's branch network. All other variables come from the pre–COVID period (2019:Q4) Call Report. Standard errors are clustered by bank headquarters state. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Large Banks	Medium-Sized Banks	Small Banks
	1	2	3
Relationship Measures			
COMMITMENTS	0.0466	0.601***	0.516***
	(0.876)	(3.914)	(7.965)
SBL	−0.0549	0.570***	0.119**
	(1.037)	(2.722)	(2.077)
CORE_DEPOSITS	0.0437*	0.0319	0.0815***
	(1.884)	(0.678)	(4.429)
Other Balance-Sheet Ratios			
C&I	0.104**	−0.212***	0.0827*
	(2.628)	(2.919)	(1.761)
LIQUIDITY	−0.0391**	−0.0591*	−0.0246***
	(2.488)	(1.745)	(3.103)
CAPITAL	−0.359*	−0.0998	0.0514
	(2.101)	(0.495)	(1.023)
Other Control Variables			
SIZE	−0.00736**	−0.0320**	0.000215
	(2.530)	(2.254)	(0.163)
AGE	0.00598	−0.0204	−0.0293***
	(1.053)	(1.076)	(8.377)
DEPOSIT_WEIGHTED_COVID_DEATH_RATE	−3.88e-05	0.000163	1.73e-05
	(1.260)	(0.796)	(0.494)
Constant	0.137**	0.633*	0.0813***
	(2.820)	(1.907)	(3.173)
No. of obs.	43	90	4,847
R^2	0.609	0.322	0.274

2. Pinning Down the Role of Relationships: Bank Lending by Market and Branch Characteristics

We have shown that bank lending during 2020:Q2 exhibits a strong link to pre-COVID measures of bank relationships. The links shift sharply between the first (pre-PPP) and second (post-PPP) quarters; the links in the second quarter are only evident in PPP lending, not in other C&I lending; and the links are strongest for smaller banks. All of these point to an important role of relationships for the supply of PPP credit. But all of these tests are just cross-bank correlations. To rule out alternative explanations due to unobserved heterogeneity across banks, we now compare PPP lending by market type (core vs. peripheral) and then by within-bank measures of the strength of the bank's relationships with local borrowers.

Table 6 reports regressions of PPP lending in core and peripheral markets separately, along with the difference between them. The regressions include the same set of explanatory variables as in Tables 3–5, but we focus only on the effects

The differences in those coefficients between the samples of medium-sized and small banks are insignificant for UNUSED_COMMITMENTS and CORE_DEPOSITS and are significant at the 5% level for SMALL_BUSINESS_LENDING.

TABLE 6

Bank PPP Lending, Relationship Measures in Core Versus Peripheral Markets

Table 6 reports regressions of bank Paycheck Protection Program (PPP) lending on pre-COVID balance-sheet characteristics, separated into markets with and without bank branches. PPP lending data are taken from the Small Business Administration, and bank characteristics are from Call Reports. Core markets are counties in which the bank owns at least one branch; peripheral markets are counties in which the bank owns no branches. Branch locations are determined from the 2019 Summary of Deposits data. The dependent variables are PPP lending in core and peripheral markets, normalized by 2019:Q4 assets, and their difference. Round 1 PPP lending includes PPP loans approved before Apr. 17, and round 2 includes loans approved after Apr. 17. Large, medium-sized, and small banks are those with >$50 billion, $10–$50 billion, and <$10 billion in assets, respectively. Regressions include (but don't report) the other control variables from Tables 3–5. Standard errors are clustered by bank headquarters state. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	All Banks			Large Banks			Medium-Sized Banks			Small Banks		
	Core Markets	Peripheral Markets	Difference	Core Markets	Peripheral Markets	Difference	Core Markets	Peripheral Markets	Difference	Core Markets	Peripheral Markets	Difference
	1	2	3	4	5	6	7	8	9	10	11	12
Panel A. All PPP												
COMMITMENTS	0.412***	0.159***	0.253***	0.0243	−0.0162	0.0405	0.435***	0.164	0.271*	0.430***	0.169***	0.261***
	(9.681)	(3.456)	(4.106)	(0.325)	(0.846)	(0.594)	(5.768)	(1.475)	(1.754)	(9.622)	(3.456)	(4.043)
SBL	0.150***	0.0326	0.117**	−0.0896	−0.0272	−0.0624	0.785***	0.0130	0.772**	0.155***	0.0193	0.136**
	(3.863)	(0.732)	(2.445)	(1.068)	(0.919)	(0.832)	(3.767)	(0.0676)	(2.381)	(3.894)	(0.422)	(2.640)
CORE_DEPOSITS	0.0665***	0.00352	0.0630***	0.0673	0.00334	0.0640	0.0263	−0.00685	0.0332	0.0651***	0.00413	0.0609***
	(6.349)	(0.217)	(4.175)	(1.622)	(0.472)	(1.723)	(0.801)	(0.297)	(0.876)	(6.331)	(0.244)	(3.859)
No. of obs.	4,366	4,366	4,366	40	40	40	81	81	81	4,245	4,245	4,245
R^2	0.342	0.078	0.060	0.509	0.581	0.419	0.610	0.161	0.327	0.372	0.077	0.063
Panel B. First Round												
COMMITMENTS	0.333***	0.134***	0.199***	0.0117	−0.0144	0.0260	0.354***	0.0519	0.302***	0.352***	0.144***	0.207***
	(10.38)	(4.778)	(5.112)	(0.198)	(0.986)	(0.488)	(4.801)	(1.569)	(3.583)	(10.32)	(4.766)	(5.033)
SBL	0.120***	0.0511*	0.0692**	−0.0431	−0.0424*	−0.000760	0.482***	0.0974	0.385**	0.125***	0.0430	0.0816**
	(3.766)	(1.908)	(2.092)	(0.555)	(1.954)	(0.0108)	(2.906)	(1.237)	(2.236)	(3.788)	(1.610)	(2.297)
CORE_DEPOSITS	0.0508***	−0.00203	0.0528***	0.0545**	0.00211	0.0524**	0.0220	−0.00739	0.0294	0.0496***	−0.00196	0.0516***
	(5.678)	(0.184)	(5.509)	(2.202)	(0.477)	(2.277)	(0.835)	(0.575)	(1.235)	(5.666)	(0.172)	(5.236)
No. of obs.	4,236	4,236	4,236	40	40	40	80	80	80	4,116	4,116	4,116
R^2	0.337	0.086	0.073	0.460	0.552	0.384	0.547	0.185	0.482	0.372	0.086	0.078

(continued on next page)

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TABLE 6 (continued)

Bank PPP Lending, Relationship Measures in Core Versus Peripheral Markets

Panel C. Second Round												
COMMITMENTS	0.0659***	0.0193	0.0466**	0.0143	−0.00168	0.0160	0.0769**	0.0607	0.0162	0.0655***	0.0193	0.0462**
	(5.250)	(1.196)	(2.403)	(0.421)	(0.229)	(0.524)	(2.043)	(1.258)	(0.238)	(5.066)	(1.122)	(2.316)
SBL	0.0326***	−0.00293	0.0355**	−0.0440	0.0150	−0.0590	0.275***	−0.0207	0.296**	0.0348***	−0.00755	0.0423**
	(3.310)	(0.167)	(2.236)	(0.765)	(0.919)	(1.252)	(2.831)	(0.251)	(2.095)	(3.492)	(0.412)	(2.564)
CORE_DEPOSITS	0.0174***	0.00277	0.0146**	0.0143	0.00135	0.0130	0.00453	−0.000818	0.00535	0.0172***	0.00323	0.0140**
	(6.136)	(0.486)	(2.653)	(0.766)	(0.417)	(0.806)	(0.324)	(0.0781)	(0.322)	(6.161)	(0.541)	(2.424)
No. of obs.	4,362	4,362	4,362	40	40	40	81	81	81	4,241	4,241	4,241
R^2	0.218	0.061	0.039	0.388	0.538	0.354	0.297	0.163	0.175	0.228	0.059	0.038

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of the relationship dimensions. We report each set of regressions first on all banks, then split based on bank size. Each of the 3 measures (i.e., COMMITMENTS, SBL, and CORE_DEPOSITS) affects PPP lending in core markets more than in peripheral ones. In fact, 2 of the 3 measures have no power to explain PPP lending in the peripheral areas. Lending in core markets most likely reflects banks' interactions with their relationship clientele, and measures of the strength of the relationships only matter in those areas. As in the earlier split by bank size, the effects are evident in small and medium-sized banks but not among the largest banks.

Table 6 also reports the same set of regressions with the dependent-variable split based on first-round versus second-round lending (Panels B and C). This split shows the same directional effects: more PPP lending by relationship banks. But it also shows much larger coefficient magnitudes during the first round. The importance to firms of having a close bank relationship thus manifests most strongly in the first round as banks put their closest customers to the front of the line in applying to the SBA. As we discussed earlier, the PPP funds ran out in just 2 weeks, leading to additional legislation to fund the second round (Figure 4).

In Table 7, we change the structure of the data to focus on how banks supply PPP lending across their core markets. In particular, we estimate regressions with the following structure:

$$\begin{aligned}(1)\qquad \log(1+\mathrm{PPP})_{i,j} = {} & \alpha_i + \gamma_j + \beta^1(\%\mathrm{DEPOSITS\_IN\_COUNTY})_{i,j} \\ & +\beta^2(\mathrm{AGE})_{i,j} + \beta^3(\%\mathrm{DEPOSITS\_FROM\_BANK})_{i,j} \\ & +\beta^4(\%\mathrm{CRA\_LOANS\_IN\_COUNTY})_{i,j} \\ & +\beta^5(\%\mathrm{CRA\_LOANS\_FROM\_BANK})_{i,j} + \varepsilon_{i,j},\end{aligned}$$

TABLE 7

PPP Lending, Within-Bank Test

Table 7 reports bank-county level regressions of Paycheck Protection Program (PPP) lending on bank-county characteristics. The dependent variable is log(1 + PPP_LENDING_AMOUNT) by the bank in the county. We include all banks merged to the Small Business Administration (SBA) PPP data, plus all banks identified as having no PPP lending from the bank Call Reports. For each bank, we include all counties in which the bank owns at least one branch. Deposit characteristics are taken from the 2019 Summary of Deposits. Community Reinvestment Act (CRA) characteristics are taken from the 2018 CRA data. Regressions with CRA data include only banks with assets over $1 billion. Large, medium-sized, and small banks are those with >$50 billion, $10–$50 billion, and <$10 billion in assets, respectively. Standard errors are clustered by bank and county. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

	All Banks		Large Banks		Mid-Sized Banks		Small Banks	
	1	2	3	4	5	6	7	8
%DEPOSITS_IN_COUNTY	0.596***	0.0571	−1.106	−1.530*	−0.0663	−0.304	0.826***	−0.00405
	(6.112)	(0.359)	(0.903)	(2.016)	(0.160)	(0.636)	(5.367)	(0.0132)
AGE	0.0851***	0.170***	0.245***	0.241***	0.104**	0.0859**	0.0492**	0.152**
	(3.958)	(5.081)	(4.598)	(5.270)	(2.344)	(2.078)	(2.024)	(2.307)
%DEPOSITS_FROM_BANK	5.845***	3.923***	5.313***	3.358***	5.810***	3.316***	5.067***	6.440***
	(19.27)	(11.42)	(11.18)	(6.616)	(9.643)	(5.853)	(7.370)	(4.688)
%CRA_LOANS_IN_COUNTY		3.840**		6.784		5.342***		8.922***
		(2.435)		(1.223)		(3.061)		(3.100)
%CRA_LOANS_FROM_BANK		4.018***		4.318***		3.570***		1.390
		(10.24)		(8.900)		(6.010)		(1.645)
No. of obs.	22,830	13,342	4,922	4,922	2,618	2,593	13,423	3,882
R^2	0.966	0.954	0.932	0.935	0.985	0.985	0.971	0.961
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

where i represents the bank, and j represents the county. The restructured data disaggregate each bank's total PPP lending in its core markets (one outcome in Table 6) into one observation for each county in which the bank owns at least one branch. The CRA lending measures, built from bank-county data collected under the Community Reinvestment Act (CRA), are only available for banks with more than $1 billion in assets. Thus, we report the models with and without the 2 variables representing bank lending.

We remove all county-level variation in equation (1) with a county fixed effect (γ_j) and all bank-level variation with a bank effect (α_i). Including the county fixed effect removes variation related to local demand for PPP loans, such as differences in exposure to COVID or other sources of variation. Including the bank fixed effect removes variation related to bank heterogeneity. Equation (1) compares PPP lending for the same bank operating in different counties. This allows us to test whether banks lend more where they raise more deposits or make more loans (β^1 and β^4), whether banks lend more where their branches are older (β^2), and whether banks lend more where their market share is higher (β^3 and β^5). If relationships affect the bank supply of PPP credit, we would expect all of these effects to load positively.

Table 7 offers strong support that banks supply more PPP credit in areas where they have stronger relationships with local borrowers. That is, banks increase their supply of PPP loans in markets where their branches are older and in markets where they lend a greater percentage of CRA loans. A bank's share of the county's total deposits is also positively related to its PPP lending (β^3), although the relative importance of a county's deposit to the bank itself is not robust across either the sample splits or the model specifications (β^1). The effect of branch age provides very strong evidence for the importance of relationships; the literature emphasizes the importance of relationship length in fostering close bank–borrower ties (e.g., Petersen and Rajan (1994)).[22]

IV. Relationship Lending, PPP Loan Supply, and Real Effects

To test how the bank supply of PPP loans affects real outcomes, we first estimate the impact of the size and structure of the local banking sector on the quantity of PPP lending at the county level. We test how these effects break down between core-market bank lending (banks with branches in the county) and peripheral-market bank lending, as well as how they break down by time (first vs. second round of PPP funds). We then report regressions of county-level real outcomes on PPP credit measures based on the pre-COVID structure of the local banking system.

A. County-Level PPP Lending

To document how local bank structure affects the overall PPP credit supply, we regress county-level PPP lending (scaled by the number of establishments with fewer than 500 employees) on 2 measures of local bank structure (controlling for

[22]In our bank-level regressions, we find the opposite. That is, younger banks make more PPP loans. This result represents variation across banks. As such, it suggests that new banks without relationship capital are using the PPP program to find new customers.

other county-level factors plausibly related to demand). The regression structure is as follows:

$$\begin{aligned}(2)\qquad \text{PPP/ESTABLISHMENT}_j = {} & \beta^1 \text{BRANCHES/ESTABLISHMENT}_j \\ & + \beta^2 \text{PREDICTED\_PPP\_LENDING}_j \\ & + \text{county demographic variables} + \varepsilon_j.\end{aligned}$$

We then subdivide county PPP lending into 4 subcomponents: based on time (first-round vs. second-round PPP) and based on core (lenders with branches in the borrower's county) versus peripheral providers of credit.

Equation (2) varies across counties (j). The outcome, PPP/ESTABLISHMENT, which we measure in thousands of dollars per establishment, averages approximately $70. BRANCHES /ESTABLISHMENT, equal to the total number of bank branches per establishment in county j, measures total banking capacity before COVID (June 2019), relative to a proxy for the number of firms eligible for PPP loans.[23] PREDICTED_PPP_LENDING equals the weighted average of each bank's predicted bank-level PPP/ASSETS in their core markets, with weights equal to bank i's share of total deposits in county j from 2019. We use the model from Panel A of Table 6 (columns 4, 7, and 10) to construct the predicted value of PPP/ASSETS for each bank; PREDICTED_PPP_LENDING thus equals a linear combination of the characteristics of the banks operating in county j. Because our bank-level model finds strong explanatory power from relationship characteristics, this variable will be high in areas where relationship lenders hold a high percentage of total deposits. Moreover, this variable is predetermined because the regression in Table 6 includes only bank covariates from the end of 2019 or earlier.

Equation (2) also includes demographic characteristics of the county (the log of the county population; the fraction of the population with a college degree or better; the fraction of the population aged 20–44), as well as measures of the strength of the local economy (the log of median income in the county from 2018 and the unemployment rate from 2019). These data come from the U.S. Census and U.S. Department of Agriculture (USDA).[24] In addition, we include the COVID death rate.[25] These variables help remove variation due to demand for PPP loans.

Equation (2) achieves two objectives. First, it allows us to assess whether or not the size of the local banking sector affects the PPP credit supply (as opposed to PPP funds flowing frictionlessly across geographies). Second, we can assess the importance of not just the size but also the structure of local banks. As we have seen, small banks, banks focusing on small business lending, and banks with high levels of unused business loan commitments originate more PPP loans; PREDICTED_ PPP_LENDING captures these effects. To summarize, if areas with more local

[23]We do not have a count of eligible firms, so we use the number of establishments with fewer than 500 employees as a close proxy. These data come from the 2018 County Business Patterns data, provided by the U.S. Census Bureau.

[24]County-level education, unemployment, and median household income data are from https://www.ers.usda.gov/data-products/county-level-data-sets/download-data/, and all other demographic data are from https://www.census.gov/data/datasets/time-series/demo/popest/2010s-counties-detail.html.

[25]Data are obtained from the Opportunity Insights Economic Tracker website (https://tracktherecovery.org).

TABLE 8

County-Level PPP Lending

Table 8 reports county-level regressions of Paycheck Protection Program (PPP) lending on county-level banking characteristics and demographics. The dependent variable is county-level PPP lending scaled by the number of establishments with fewer than 500 employees. Total PPP lending includes all PPP loans in the SBA data; the division into core versus peripheral lenders includes only loans that we were able to match to Call Report lenders (~94.8% of the total). Core lenders are banks that have at least one branch in the county, and peripheral lenders are those without a branch in the county. Round 1 PPP lending includes PPP loans approved before Apr. 17, and round 2 includes loans approved after Apr. 17. BRANCHES/ESTABLISHMENT is the ratio of total branches to establishments with fewer than 500 employees as of 2019. PREDICTED_PPP_LENDING equals the weighted average of each bank's predicted bank-level PPP/ASSETS in their core markets, with weights equal to each bank's share of total deposits in the county from 2019. Standard errors are clustered by state. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

		PPP/ESTABLISHMENT			
		Core Lenders		Peripheral Lenders	
	PPP/ESTABLISHMENT ($thousands)	First Round	Second Round	First Round	Second Round
	1	2	3	4	5
BRANCHES/ESTABLISHMENT	998.5***	215.1***	28.33	529.2***	151.0**
	(200.9)	(45.59)	(18.92)	(117.3)	(58.34)
PREDICTED_PPP_LENDING	110.0	285.1***	−8.966	−112.1**	−36.45*
	(73.86)	(20.47)	(13.07)	(49.94)	(21.57)
County-level demographic variables		Included, not reported			
No. of obs.	3,062	3,062	3,062	3,062	3,062
R^2	0.075	0.233	0.282	0.137	0.107

bank branches receive a greater supply of PPP loans, then $\beta^1 > 0$. If the type of bank matters, then $\beta^2 > 0$.

We use equation (2) as a first-stage regression to show that variation in predetermined measures of banking structure affects the quantity of PPP credit. To document that these are valid measures of supply (rather than demand), we split the outcome based on PPP lending from banks located in the county (core-market banks) versus PPP lending by banks not located in the county (peripheral-market banks). Lending from peripheral-market banks will increase with PPP demand. Hence, if there is no positive effect of BRANCHES/ESTABLISHMENT or PREDICTED_PPP_LENDING on lending by peripheral banks, then we can rule out a spurious correlation with PPP demand.

Column 1 of Table 8 reports estimates of equation (2). We find strong evidence that areas with more local bank branches receive more PPP loans, that is, $\beta^1 > 0$ (significant at 1% level). The magnitude is also substantial. A 1-standard-deviation increase in BRANCHES/ESTABLISHMENT (= 0.02), for example, is associated with an increase in PPP lending of approximately \$18,000 per establishment (= 0.02 × 888.6 × 1000), or a little less than 30% of the mean (= ~\$70,000). PREDICTED_PPP_LENDING has a positive but insignificant coefficient, however.

Columns 2–5 of Table 8 separate the outcome between the first and second rounds of PPP lending (recall Figure 4) and between core versus peripheral markets. This 4-way split suggests that both the size of the local banking system (BRANCHES/ESTABLISHMENT) and its structure (PREDICTED_PPP_LENDING) increase the quantity of PPP loans in the first round (column 2). Columns 3–5 help us assess the (identification) claim that the banking-structure variables capture PPP supply. In contrast to PREDICTED_PPP_LENDING, BRANCHES/ESTABLISHMENT covaries positively with PPP loans from peripheral lenders in both the first and second rounds. This suggests a critical identification concern: Areas with more bank branches (pre-COVID) contain more firms reliant on bank credit (i.e., greater demand for PPP loans). Hence, the number of bank branches *cannot be used* to assess the PPP credit supply. In contrast, PREDICTED_PPP_LENDING loads negatively in columns 3–5, meaning that some firms, unable to borrow locally in the first round (because their market contains too few relationship lenders), were able to get credit from peripheral banks. Thus, PREDICTED_PPP_LENDING predicts early access to the PPP program (column 2). Borrowers in areas with higher PREDICTED_PPP_LENDING move to the "front of the line" and receive credit early from their relationship lenders.

B. Small Business Revenues, Local Spending, and Unemployment

To test whether the PPP credit supply from relationship lenders has real effects, we model 3 outcomes: daily SMALL_BUSINESS_REVENUE, daily LOCAL_SPENDING, and monthly UNEMPLOYMENT_RATE. We construct panel data at the county-time level, from the beginning of 2020 through July. This sample incorporates a pre-COVID period, a period of transition in which the effects of COVID pushed financial markets into turmoil (most of March), and a period in which policy steps from the CARES Act had gone into effect (April and the subsequent months). Our model tests how measures of local demographics, local pre-COVID economic variables, and the PPP credit supply affect real outcomes across these shifting periods. Specifically, we estimate the following model:

$$\text{(3)} \quad \mathrm{Y}_{j,t} = \alpha_{t,s} + \gamma_j + \Sigma\beta^k \left(I_t^{\,k} \times \text{PREDICTED\_PPP\_LENDING}_j\right) + \Sigma\gamma^k \left(I_t^{\,k} \times \text{DEMOGRAPHIC\_AND\_ECONOMIC\_CONTROLS}_j\right) + \varepsilon_{\,j,t},$$

where j represents county, and t represents time (either day or month). $Y_{j,t}$ represents each of our 3 outcomes. We remove aggregate shocks with the state-time effect ($\alpha_{t,s}$) and all cross-county heterogeneity with the county effect (γ_j). All county characteristics, including PREDICTED_PPP_LENDING, vary only in the cross section, so the county effect absorbs their direct impact on outcomes.

We focus on how PREDICTED_PPP_LENDING affects outcomes as the COVID crisis emerges and then as the policy actions come online. In addition, we control for other county-level variables to absorb as much variation in demand for PPP credit as possible, as well as the effects of the COVID crisis on outcomes. Hence, we interact each county characteristic with I_t^k, defined as 5 monthly indicators.[26] The first indicator (MARCH) equals 1 prior to the beginning of the PPP program but after the onset of the COVID crisis, and 0 otherwise.[27] The last 4 indicators correspond to calendar months during the period in which the PPP program distributes funds. The coefficients β^k test for systematic shifts in the impact of PREDICTED_PPP_LENDING (and the other county characteristics) during these 1-month periods, relative to the omitted period (January and February).

[26]The PPP program closed to new applications on Aug. 8, just a few days after the end of our sample, so we end our analysis in July.

[27]The World Health Organization declared COVID a global pandemic on Mar. 11, 2020.

If the relationship lenders help firms, then β^k ought to be positive for both SMALL_BUSINESS_REVENUE and LOCAL_SPENDING during April–July and negative for UNEMPLOYMENT_RATE. The effects measured during the CRISIS period represent "placebo" tests because the PPP program had not yet come online then. This helps us assess the plausibility of the model.[28]

Equation (3) represents a reduced form, which directly links a supply instrument (PREDICTED_PPP_LENDING) to the real outcomes. We could have structured this analysis as an instrumental-variables model, with PPP/ESTABLISHMENT modeled as the endogenous regressor. However, if the structure of the local banking system affects economic outcomes in ways that go beyond the PPP program, then these instruments might fail the exclusion restriction. Although this may be true, and although additional effects cannot be fully ruled out, lending patterns suggest otherwise. First, the PPP program dominates new credit originated during Apr.–July 2020. For example, non-PPP C&I lending fell during the second quarter of 2020 (Table 1). Second, as we will see, the time-series pattern of the effects of banking lines up with the timing of the PPP program.

Table 9 reports the estimates of equation (3). We find little impact of PREDICTED_PPP_LENDING on either SMALL_BUSINESS_REVENUE or LOCAL_SPENDING. Sign patterns are positive, consistent with benefits, but with minimal joint statistical significance (F-statistics = ~1 for the April–July coefficients). In contrast, we find very strong statistical evidence that UNEMPLOYMENT_RATE is lower in markets with more relationship lenders (i.e., higher PREDICTED_PPP_LENDING). Coefficients become strongly negative in May, and they increase in magnitude in June and July, with high joint statistical significance (F-statistic = 8.13). The time patterns of our estimates in the reduced form are consistent with our core arguments. That is, there is no evidence of "pre-trends" in the data. The coefficient on PREDICTED_PPP_LENDING is small and not statistically significant in Mar. 2020, as it should be because the PPP program had yet to begin.[29]

Although counties with higher PREDICTED_PPP_LENDING do experience less unemployment after the advent of the PPP program, the economic impact is small. For example, increasing PREDICTED_PPP_LENDING by 1 standard deviation (= 0.014) lowers the unemployment rate in June by just 0.21 percentage points (= –0.014 × 15.2); this decline is dwarfed by the average increase in unemployment of 7.6 percentage points between March and April. Moreover, we find no broader benefits, either to small businesses themselves (in terms of sales or revenues) or in terms of total spending. The small economic magnitude likely reflects the fact that the second round of PPP funding was sufficiently generous that all firms demanding these loans eventually received them. That said, the evidence does suggest that relationship lending, by giving firms early access to the PPP program, did help these firms avoid laying off workers.

[28]We double cluster by time (or state-time in the case of the unemployment rate, due to the small number of time units) and county to construct standard errors.

[29]Mar. 2020 represents a fairly strong placebo period because banks were important during that time in alleviating the stresses on large firms resulting from the disruptions in the money markets and the bond market. Thus, if we observe no effects on local outcomes before April, this supports the claim that the effects observed after April in fact stem from the PPP program.

TABLE 9

County-Level Economic Outcomes and PPP Lending by Local Banks

Table 9 reports county-time panel regressions of real economic outcomes on measures of the size and structure of local banks. SMALL_BUSINESS_REVENUE and TOTAL_SPENDING come from https://tracktherecovery.org; see Cherry et al. (2020). Monthly unemployment rates by county are from the Bureau of Labor Statistics. PREDICTED_PPP_LENDING equals the weighted average of each bank's predicted bank-level lending from the Paycheck Protection Program (PPP)/ ASSETS in their core markets, with weights equal to each bank's share of total deposits in the county from 2019. Standard errors are clustered by county and time in columns 1 and 2 and by county and state-time in column 3. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The *F*-statistic tests that PREDICTED_PPP_LENDING times the 4 time interactions from April onward is equal to 0.

	SMALL_BUSINESS_REVENUE	LOCAL_SPENDING	UNEMPLOYMENT_RATE
	1	2	3
MARCH × PREDICTED_PPP_LENDING	0.348	0.282*	−0.724
	(0.298)	(0.154)	(0.994)
APRIL × PREDICTED_PPP_LENDING	0.0421	0.199	2.653
	(0.421)	(0.234)	(4.585)
MAY × PREDICTED_PPP_LENDING	0.435	0.346	−8.624**
	(0.450)	(0.268)	(3.534)
JUNE × PREDICTED_PPP_LENDING	0.533	0.0674	−13.20***
	(0.466)	(0.308)	(3.155)
JULY × PREDICTED_PPP_LENDING	0.205	0.189	−12.97***
	(0.479)	(0.264)	(3.151)
F-test	0.93	0.98	8.06
P-value	0.450	0.420	0.001
County fixed effects	Yes	Yes	Yes
State × time effects	Yes	Yes	Yes
Frequency	Daily	Daily	Monthly
Control variables:	CALENDAR_INTERACTION × BRANCHES/ESTABLISHMENT		
Control variables:	CALENDAR_INTERACTION × ln(POPULATION)		
Control variables:	CALENDAR_INTERACTION × COVID_DEATH_RATE		
Control variables:	CALENDAR_INTERACTION × COUNTY_MEDIAN_INCOME (2018)		
Control variables:	CALENDAR_INTERACTION × SHARE_COLLEGE		
Control variables:	CALENDAR_INTERACTION × SHARE_20_TO_44_YEARS_OF_AGE		
Control variables:	CALENDAR_INTERACTION × LOCAL_UNEMPLOYMENT_IN_2019		
No. of obs.	430,519	313,118	21,483
R^2	0.578	0.677	0.918

V. Conclusion

This article analyzes the role of banks as the primary conduit of funds for the PPP. We find that PPP lending by banks increases with traditional measures of relationship lending: larger for small banks, increasing in prior experience in the local market, increasing in commitment lending, and increasing in core deposits. The traditional rationale for bank relationships, which is access to soft information, thus mitigating asymmetric information problems, cannot explain our findings because banks face no credit risk in making PPP loans. Thus, our results suggest a new benefit to firms of close ties to their banks, which are often the key conduit for access to government subsidies. Using our model of bank-level lending, we build a local supply measure that reflects the structure of the banking systems. We find that increases in this predicted PPP lending, which reflect the presence of relationship-oriented banks prior to COVID, lower local unemployment.

Our results point to an inefficiency in the distribution of PPP funds: Firms with banking relationships receive earlier access to credit, irrespective of merit. Distributing the $525 billion in funds so quickly, just 1 month, could only be achieved using the human capital employed by the banking system. Government interventions or bailouts have often historically worked through the banking system.

We have seen this not only with the PPP program but also in other ways in which the Federal Reserve intervened during the COVID crisis, in its interventions during the 2008 global financial crisis, and also in its actions to stem bond-market disruptions during 1998. Why do government interventions work through banks, rather than just helping whatever economic entity is most distressed? The answer may reflect an unpleasant trade-off between the short-term benefits of interventions (e.g., ending a financial panic) versus the longer-run moral-hazard costs. Using the banking system as the conduit may be a way to limit the scope of interventions and thus limit the associated moral-hazard costs.

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