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Small Bank Financing and Funding Hesitancy in a Crisis: Evidence from the Paycheck Protection Program

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ABSTRACT

We study the delivery of subsidized financing to small firms through the Paycheck Protection Program (PPP). Smaller firms are less likely to gain early PPP access, an effect attenuated in small banks and firms with prior lending relationships. Their more even treatment offers a new rationale, beyond traditional soft information arguments, for why small businesses pair with small banks. We also detect a "funding hesitancy" in PPP uptake by small businesses, partly reflecting their wariness of the extensive, subjective government powers to investigate PPP recipients. We discuss the implications of the results for research and policies on small business financing.

Keywords: Bank Relationships, Covid-19, Coronavirus, Paycheck Protection Program, PPP, SBA, Small Business Lending

JEL classification: G32, G38, H81, E61

1. Introduction

The Covid-19 pandemic has been a black swan event. It has resulted in the loss of over 3.5 million lives. It has also severely impacted livelihoods due to a widespread, speedy, and deep economic contraction. For instance, U.S. GDP contracted by a third and unemployment jumped from 4% to 15% within a quarter. Small businesses have been hit particularly hard (Chetty, Friedman, Hendren, and Stepner, 2020). Moreover, they are key sources of employment and growth, so helping them has been a policy priority.[1]

Fiscal stimulus has been the key instrument for helping small businesses. In the U.S., its centerpiece is the $669 billion Paycheck Protection Program (PPP), which provides extraordinarily inexpensive financing for small firms. Loans are disbursed through a simple application process. Proceeds used in eligible ways are forgiven while the rest converts to a 5-year 1% loan – attractive terms for *any* firm. Not surprisingly, small businesses rushed to get PPP funding. The initial PPP funding of $349 billion was quickly exhausted. The program closed, reopening after 10 days after a fresh appropriation of $320 billion.

We exploit the fact that the initial days of the PPP were a large-scale shock for both the banks used to pipe PPP funding and the small businesses the PPP targets. We study two related issues. To motivate the first question, observe that banks were overwhelmed in the initial PPP stages, both due to the aggregate shortage of PPP funds and the surge in applications for this inexpensive funding. Banks were forced to prioritize clients. This setting provides a rare - and clear - window into banks' allocation priorities when facing resource constraints - a subject of importance, given that crisis tend to recur, and banks periodically face resource constraints. Our particular focus is on the differences between small and big banks.

We find that there are significant differences between how big and small banks prioritize small clients: big banks are more likely to prioritize larger clients early. We show that this effect is attenuated and sometimes reversed for small banks, who extend more even treatment to their smaller clients.[2] We further investigate this pattern using a large database of UCC filings to identify bank-firm lending relationships. We find that such relationships also help firms gain early PPP access. We find little evidence that relationships with big banks help more – if anything, small bank relationships help firms get early PPP access, especially with

[1]Small businesses account for 60.6 million jobs, or 47.1% of the total U.S. employment in 2020. See "2020 Small Business Profile at `https://cdn.advocacy.sba.gov/wp-content/uploads/2020/06/04144224/2020-Small-Business-Economic-Profile-US.pdf`.

[2]For anecdotal evidence of "concierge treatment," see, e.g., "Banks Gave Richest Clients 'Concierge Treatment' for Pandemic Aid," The New York Times, April 22, 2020 at `https://www.nytimes.com/2020/04/22/business/sba-loans-ppp-coronavirus.html`. Our study presents formal evidence and shows its variation across big and small banks, an issue that has attracted less attention.

small bank lenders. The more even treatment of small firms vis-a-vis large firms by small banks offers a new rationale for why small businesses tend to borrow from small banks. This rationale is different from and adds to the more traditional explanations based on soft information, which, as we discuss later, has little role in PPP lending.

The second part of our analysis focuses on the small businesses targeted by the PPP. As these small firms are highly constrained even in normal times, they should welcome the PPP, which delivers inexpensive funding, does so promptly, and as we show later, has positive valuation effects. However, we find a "funding hesitancy" among PPP recipients, most starkly manifest in the decisions of several firms to return PPP funds without using them and the *positive* valuation effects associated with PPP return. Further empirical tests suggest that funding hesitancy is partly due to wariness of government powers to investigate PPP recipients, in turn likely due to subjectivity in its standards and scope as well as the absence of safe harbors. We discuss the policy implications of these results for the design of government aid programs.

We construct four datasets. The first is the December 2020 SBA PPP data release comprising 5.2 million PPP borrowers. The second dataset includes publicly listed PPP borrowers identified through algorithmic searches of 8-K and 10-K filings. The public PPP sample has two sets of benefits. One, we have firm-specific information for controls and return data to compute program valuation effects. As importantly, this sample lets us identify PPP returners and address issues relating to funding hesitancy. The SBA PPP dataset does not identify returners. In both samples, we define early borrowers as those approved for PPP before April 17, 2020, the initial program PPP closure date.

The third and fourth datasets identify bank relationships. Our initial source is the DealScan database, which, however has limited coverage of small firms. The other dataset comprises Uniform Commercial Code (UCC) security interest filings of banks through December 2020. These data include 32.5 million observations and significantly expand the coverage of small firm bank relationships (Gopal and Schnabl, 2020).

We turn to the results on early access. From the viewpoint of demand for PPP by firms, smaller firms should access PPP funds sooner if they are more constrained, weaker, and less resilient to the Covid-19 shock. However, we find that *larger* firms tend to gain early PPP access. For example, in the public PPP sample, early borrowers are larger, with mean (median) book value of assets of \$120.3 (\$39.2) million compared to \$99.8 (\$23.3) million for late borrowers. We find similar results when we use the PPP loan amount as a size proxy, in the SBA PPP sample, and in regressions with controls. Large borrower prioritization is a robust feature of the data.

We next analyze the variation in large firm PPP access across small and big banks. We define big banks as the top 10 banks according to asset size. Other banks are small.Big banks tend to grant early access for larger firms, an effect attenuated in small banks. For example, in big banks, early PPP borrowers are 2-3 times larger than late borrowers: the mean (median) book values equal \$144.2 (\$55.11) million versus \$61.36 (\$18.7) million, respectively. For small banks, the early and late borrowers are closer in size with mean (median) book values of \$82.4 (\$36.4) million and \$86.7 (\$26.9) million, respectively. Regressions with controls confirm the results for the public and the SBA PPP samples.

We turn to the role of prior bank relationships. Identifying relationships is straightforward in the DealScan data and for public firms using COMPUSTAT identifiers. The process is less simple with the UCC filings and for the SBA PPP dataset as the linking identifiers are firm and bank names. Besides variations in spelling, we must contend with bank mergers in mapping the legacy UCC bank names to those in the PPP data. We use fuzzy matching followed by extensive manual interventions to cross-walk the 33 million observations in the UCC dataset with the 5.2 million observations in the SBA PPP dataset.

We find that bank relationships, particularly with small banks, matter. Firms applying for PPP with small banks tend to gain early access but a prior small bank relationship has its own beneficial effect. For example, firms that have no UCC or DealScan relationship, early PPP borrowers are twice as large as late borrowers, with median (mean) book values of \$64 (\$35) million versus \$38 (\$15) million, respectively; these figures are \$248 (\$161) million and \$151 (\$69) million for firms with big bank relationships. The patterns reverse sharply when borrowers have small bank relationships. Here, early firms are *smaller* than the later firms: \$119 (\$43) million versus \$178 (\$94) million, respectively. Thus, a prior small bank relationship helps mitigate the pattern of greater early access to PPP for larger firms. The results carry over to the larger SBA PPP sample.

The results have interesting implications for banking research. A distinct pattern in the data is that small firms tend to pair with small banks. This is seen in the Federal Reserve's Survey of the Terms of Bank Lending to Businesses (STBL), small business lending data in Call Reports, and most recently in the 2018 FDIC Survey of Small Business Lending. Related research includes Berger, Saunders, Scalise, and Udell (1998) and Berger, Miller, Petersen, Rajan, and Stein (2005). Stein (2002) provides a theory for small bank – small firm pairing. He argues that soft information, which is critical in small business lending, is hard to transmit up bank hierarchies typical of large banks. Thus, in small business lending, it is optimal to colocate decision making and information gathering, as in small banks.

Our PPP evidence offers an alternative explanation for why small businesses tend to bank with small banks. In the initial PPP period, a surge in PPP demand coupled with aggregate shortage of PPP funding forced banks to prioritize clients. We find that in this period, small banks tend to be more responsive to small businesses. The finding suggests that in big banks, small businesses experience a "small fish in big pond" effect that is mitigated in smaller banks for whom small business lending is a mainstay of their lending portfolio. This explanation does not rely on soft information considerations, which has little role here given government guarantees of PPP loans as we discuss in detail later.

The second issue we study concerns PPP uptake. As motivation, we note that the firms targeted by PPP, small businesses, face severe financial constraints even in normal times (Petersen and Rajan, 1994; Whited and Wu, 2006; Hadlock and Pierce, 2010; Banerjee and Duflo, 2014). PPP should be welcome news for such firms. It is immediately available and it is extraordinarily inexpensive, with costs range from -100% (with full forgiveness) to a maximum of 1%. Moreover, markets reward firms that take PPP. Average uptake valuation effects exceed 1% and the treatment effects are positive after econometric adjustments for heterogeneity in pandemic period returns and partial anticipation of PPP uptake.

Yet, we find some reluctance by firms to take PPP funds, which we call "funding hesitancy." Perhaps the sharpest evidence of hesitancy is our finding that over 100 public firms that get PPP funds simply return the funds without using them. Moreover, while one might expect returning cheap funding should decrease share prices, reflecting lost financing subsidies, returners experience *positive* valuation effects averaging 3%. Markets appear to reward firms that return PPP!

What might explain this aversion to PPP funding? Direct costs of PPP funds are clearly implausible as these funds are far cheaper than alternatives from banks or the market. The direct costs from PPP restrictions (e.g., on layoffs) are also implausible. For firms that find it difficult to comply, the worst case scenario is that PPP forgiveness is lost and PPP becomes a 1% loan, still far less expensive than alternatives. Perhaps then, rather than direct costs, there are some indirect costs that prompt PPP return. What could their nature be?

A significant indirect cost of PPP comes from the threat of ex-post government investigations of PPP recipients. Three features make these costs salient. One, investigation windows are very long – at least 6 years from PPP disbursement. Two, the standards for initiating investigations, their scope, and the process are highly subjective, leaving a lot of discretion in government hands.[3] Finally, the program provides no safe harbors that shield PPP recipients from ex-post investigations. Given this lack of clarity and the fungibility of funds, it is easy to attribute *any* use of funds to PPP funding, making recipients fodder for sensationalist media coverage.[4] Should these ambiguities concerning investigations mat-

[3] An example of the ambiguity is the need to certify that "[PPP is] ... necessary taking into account current activity... and access to other sources of liquidity in a manner not significantly detrimental to the business." These are clearly subjective standards.

[4] Consider the story in Washington Post on September 26, 2020 "Publicly traded firms paid dividends,

ter to firms? Research certainly suggests so: Simply being an investigation target triggers shareholder wealth losses. Capital raising in its shadow is difficult and, moreover, senior executives and directors face negative consequences in the labor market.[5]

We conduct tests to assess to explore these indirect costs. One set of tests looks at the decision to return PPP, using the public PPP sample in which returners are identified. If larger loans are more likely to be investigated by the government, PPP returns should be more likely for larger loans. Relatedly, SBA rules indicate that PPP loans exceeding $2 million and outstanding after May 18, 2020 are subject to audit. Two implications fall out of this observation. One, PPP returns may be more likely above the $2 million cutoff, which we can examine for the public PPP sample. Two, loan application probabilities should exhibit a discontinuity around $2 million. This test can be done for the larger SBA sample. A further implication is that the discontinuity should be asymmetric before and after May 18, 2020, when the $2 million cutoff became salient. The results broadly support the view that government investigation threats are at least partially responsible for funding hesitancy.

The rest of the paper is organized as follows. Section 2 discusses background information and relevant literature. Section 3 describes the datasets used in the study. Section 4 analyzes early PPP access. Sections 5 and 6 discuss the uptake of PPP, relevant treatment effects estimation, and funding hesitancy. Section 7 concludes.

2. Background

2.1. The PPP Program Architecture

Figure 1 gives the timeline leading up to the passage of the $669 Paycheck Protection Program (PPP). This original "CARES" Act included a $349 appropriation for PPP. It was proposed on January 24, 2020, passed by the legislature on March 25, 2020 and March 26, 2020, and signed into law by the U.S. President on March 27, 2020. The initial PPP allocation of $349 billion was exhausted quickly by April 16, 2020, when the program stopped accepting new applications. The PPP resumed accepting applications on April 27, 2020 after an additional $320 billion appropriation under the Paycheck Protection Program and Health Care Enhancement Act of 2020 signed on April 24, 2020.

The next significant milestone was May 18, 2020. As announced in late April–early May, firms returning PPP before this date would not be subject to audit. The next milestone was

bought their own stock after receiving PPP loans to pay employees" at `https://www.washingtonpost.com/business/2020/09/24/dividends-buybacks-ppp-loans`.

[5] Jarrell and Peltzman (1985), Alexander (1999), Haslem, Hutton, and Smith (2017), Karpoff, Lee, and Martin (2008), Fich and Shivdasani (2007), Murphy, Shrieves, and Tibbs (2009), Lin and Paravisini (2011).

June 2, 2020, when the PPP Flexibility Act (PPPFA) was passed, which altered program rules significantly. 96% of PPP proceeds were disbursed prior to this date within a relatively homogenous regulatory regime. Our sample focuses on this period. The program expired on August 8, 2020. It disbursed $525 billion to 5.21 million borrowers.

Application Process: The PPP is a forgivable, collateral-free loan program administered through the Small Business Administration (SBA), a federal agency that guarantees the PPP loans. Borrowers apply through an approved financial institution, provide documentation relating to eligible expenses such as payroll and allowed overhead, and make necessary representations and certifications. After SBA approval, funds are disbursed by the banks.

Eligibility: Eligible borrowers are small firms as defined in the CARES Act. Standards include a principal place of residence in the U.S., being in operation before February 15, 2020, having fewer than 500 employees, or other standards, e.g., as under Small Business Act, 15 U.S.C 632. PPP eligibility is not conditioned on the credit risk of borrowers.

Amount and Terms: The maximum PPP loan is $10 million per eligible entity. Forgiveness applies to amounts spent as per the program rules. The principal not forgiven turns into a loan with a 5-year maturity if made on or after June 5, 2020 and a 2-year maturity otherwise unless both the lender and borrower agree to a 5-year term.

Spending PPP funds: The PPP incentivizes early spending of proceeds. Banks must make loans within 10 days of approval. Forgiveness applies to eligible payroll spent within time periods laid out in the Act, initially 8 weeks and extended later to 24 weeks under the June 2, 2020 PPPFA. Forgiveness is reduced if there are layoffs.

Certification: Borrowers receiving PPP funds must certify that "... the current economic uncertainty makes the loan necessary to support ongoing operations" and as per PPP Rule 31 issued on June 25, 2020 "... taking into account ... their ability to access other sources of liquidity" in a manner that is not significantly detrimental to the business.

Lender Responsibilities and Fees: Lenders submit applications on behalf of borrowers and fund the loans. The rules are quite explicit that lenders should rely on borrower certifications and representations to submit applications. Thus, the traditional soft information production role of banks is moot under PPP. Moreover, fraud becomes a concern only when banks undertake willful actions to actively create and abet it. Lender fees equal 5% for loans up to $350,000, 3% for loans between $350,000 and $2,000,000, and 1% for loans of at least $2,000,000. An April 17, 2020 ruling lets lenders sell PPP loans.

Powers to Investigate: The SBA retains the right to review all loans for eligibility. It clarified that loans over $2 million would be audited but smaller loans may not be. If a firm is found ineligible in an audit, it needs to return principal plus interest and is subject to any other remedies that the SBA may seek. Firms that repay PPP loans in full by May 7, 2020

– later extended to May 18, 2020 – are not subject to investigations. These and related rules were clarified by the SBA at different times and attracted attention. While the clarifications help clarify SBA rules, the absence of formal safe harbors and the repeated pronouncements on the topic can raise the investigative threat more salient for PPP recipients.

2.2. Related Covid-19 Research

The Covid-19 pandemic has attracted a vast literature. For a curated collection of several hundred Covid Economics papers, see the website maintained by Center for Economic Policy and Research.[6] An extended review of the banking research related to Covid-19 is in Berger and Demirguc-Kunt (2021). We briefly review some of the work relevant to our study.

Several studies examine the impact of Covid-19 on firm outcomes. Granja, Makridis, Yannelis, and Zwick (2020) show in an ongoing real time analysis that the PPP has had limited impact on labor market outcomes. Kim (2020) argues that the impact is greater if one accounts for lender constraints. Cororaton and Rosen (2020) analyze the characteristics of 424 public PPP applicants, and in later versions, follow our approach and verify a subset of our results on PPP announcement and returns in Sections 5 and 6. Li and Strahan (2020) show that the PPP supply alleviates Covid-related unemployment shocks, using an identification strategy at a geographic level based on the structure of the local banking sector. Bartik, Cullen, Glaeser, Luca, Stanton, and Sunderam (2020) and Bartlett and Morse (2020) find positive impacts on very small businesses. While assessing PPP impact is not our main focus, we provide some evidence based on stock market data.

Theoretical work on PPP funding includes Hanson, Stein, Sunderam, and Zwick (2020), who discuss the government as a venture capitalist of last resort. Other literature addresses financing concerns and stock market patterns in the pandemic. Acharya and Steffen (2020) and Acharya, Engle, and Steffen (2020) highlight a Covid period "dash for cash." Over 95% of our sample includes unrated firms, who do not display this dash for cash. The role of FinTech lenders in PPP supply is addressed by Erel and Liebersohn (2020). The unusual nature of Covid-19 period stock returns is the focus of Acharya et al. (2020), Fahlenbrach, Rageth, and Stulz (2020), Baker, Bloom, Davis, Kost, Sammon, and Viratyosin (2020). We account for this issue in estimating valuation effects.

Relevant to our work on funding hesitancy is the literature on the penalties suffered by firms due to government investigations of their conduct. Prominent examples include Jarrell and Peltzman (1985), who study FTC investigations into false or misleading advertising and Alexander (1999) who analyzes penalties in a range of violations in government contracts.

[6] See https://cepr.org/content/covid-economics-vetted-and-real-time-papers-0.

See Haslem et al. (2017) for a recent review of this line of research. The implications of such investigations for firms, their managers, and directors are the subject of Karpoff et al. (2008), Fich and Shivdasani (2007)), Murphy et al. (2009), and Slutzky (2020). Of special interest is Armour, Mayer, and Polo (2017). Using UK data from 2001 to 2011, it finds that stock market penalties are 9 times the actual fines imposed on companies for violations. The threat of government investigations thus goes beyond possible fines, which can explain firms' aversion to such investigations and the positive valuation effects from its release.

3. Data

We use multiple datasets for our study. One is the SBA PPP release in December 2020, which covers 5,156,850 PPP recipients. Borrowers and lenders are identified by their names as recorded in the PPP application. Our second and third datasets identify bank-firm relationships. We start with the DealScan database. However, given its limited coverage of smaller and private firms, we turn to the data on bank relationships identified via security interest filings under the Uniform Commercial Code (UCC). See Gopal and Schnabl (2020). We obtain a version of the UCC data updated to December 2020.

The UCC data provider also matched PPP recipients to its proprietary dataset on all small firms. This list includes 1,469,167 PPP recipients. We call this intersection the "SBA PPP" dataset. This dataset is useful in tests involving bank relationships. It seems to be a more conservative choice for the overall universe of firms used for assessing bank relationship effects. That said, the results are similar with the overall SBA PPP dataset, so the ultimate choice on what to present and what to keep for robustness is immaterial.

The next dataset includes publicly listed PPP recipients. We obtain this dataset by hand-collecting data from firms' SEC filings – rather than the SBA PPP release – for three reasons. One, the SBA PPP release does not cover or identify PPP returners. Thus, the funding hesitancy tests are infeasible with the SBA release. Two, the tests on stock market effects require dates on which the markets learn of PPP uptake or return, which are available in the SEC filings. Finally, we have balance sheet and income statement data for public firms, which are not available in the private PPP recipient dataset released by the SBA.

3.1. SBA PPP Dataset

The SBA has three releases of PPP borrowers between June and December 2020. The earlier releases did not identify exact loan amounts. The December 2020 release does so. We use it in our tests. Inspecting the sample reveals that there a very large number of very small loans; we test and verify that our results are not artifacts of these observations. The SBA provides data on recipient types, which could be corporations (29.1%), limited liability companies (28.2%), sole proprietorships (15.9%), Subchapter S corporations (13.6%), non-profit organizations (3.5%), and other business types (9.8%). We exclude 99,460 financial firms and REITs. We identify and focus on the subsample of 1,498,552 firms that are incorporated as corporations. This makes the sample homogeneous and eliminates biases from the late entry of some firms (e.g., non-employers, proprietarships) that became eligible later. Including them would mechanically show that small firms have late PPP access.

Table 1 reports the overall statistics for this sample (Panel A). It shows that the SBA overall disbursed \$523 billion in PPP funding to 5.2 million borrowers, about 78.2% of the PPP appropriation of \$669 billion.[7] Of this, \$320 billion (61%) is disbursed to 1.6 million (31%) of the borrowers during the initial rush period from April 3, 2020 to April 16, 2020. Thus, the initial PPP disbursements are to larger borrowers.

3.2. *Public PPP Applicants*

We download all company 8-K, 10-K, and 10-Q filings with the Securities and Exchange Commission (SEC) filed between April 1, 2020 and September 30, 2020. To identify PPP recipients, we employ a combination of computer code and a manual procedure. The code searches for keywords such as "PPP," "Paycheck Protection," and "CARES" in the filings. We read through the candidate documents to identify PPP recipients and collect other data such as loan amounts and filing dates and cross-verify some through news releases. We follow the same procedure for firms that returned PPP loans. 48.2% of companies report their PPP loans in 8-Ks followed by 40.1% in 10-Qs. Most 8-K filers (63.6%) report PPP loans under "Item 1.01: Entry into a Material Definitive Agreement."[8]

Our initial sample includes 1,233 PPP loans provided to 1,020 public PPP borrowers (Table 2). After matching to COMPUSTAT, excluding financial firms and firms that apply after the PPPFA, the usable sample for most cross-sectional tests is about 682 public PPP borrowers. Many (75.2%) of these firms have nominal share prices of less than \$5. As stock returns for these firms may be unreliable, especially at high frequency, we interact return-based explanatory variables (e.g., volatility) with a penny stock dummy variable.[9]

[7] The often cited official number, \$525 billion, differs due to variations across SBA releases.

[8] About 21.5% of firms use "Item 2.03: Creation of a Direct Financial Obligation or an Obligation under an Off-Balance Sheet Arrangement of a Registrant." Other items include "Item 8.01: Other Events" (7.2%), "Item 9.01: Financial Statements and Exhibits" (3.9%), "Item 2.02: Results of Operations and Financial Condition" (2.3%), and "Item 7.01: Regulation FD Disclosure" (1.3%). In 10-Q's and 10-K's, disclosures are mostly in the "Subsequent Events" section (52.8%).

[9] As due diligence, we try to match our public data set to the SBA PPP release. We match 72% of the firms

To assess the locus of public PPP applicants within the universe of listed small firms, we construct a pool of small firms who did not apply for PPP funds. These are COMPUSTAT firms with fewer than 500 disclosed employees as of the fiscal 2019 or the prior year if missing, excluding financials or SPACs. The final non-applicant sample includes 1,452 small firms in COMPUSTAT that did not apply for PPP.[10] Financial characteristics are from COMPUSTAT and returns are based on adjusted stock prices downloaded from Yahoo! Finance. Credit ratings data are from Standard & Poor's or Mergent and distance-to-default data are from NUS RMI Credit Research Initiative. We match PPP borrowers and their subsidiaries to DealScan and UCC. The data on subsidiaries are from Nexis Uni.

3.3. Identifying Firms Returning PPP Funds

We identify 123 public PPP borrowers that return PPP funds without using them. 58.1% of these firms disclose returns in 8-Ks and 34.4% do so in 10-Qs. In most cases, the information pertaining to PPP loan repayments is contained in "Item 9.01: Financial Statements and Exhibits" of 8-K reports (48.9% of 8-K filings).[11] In 10-Q reports, PPP loan repayments are most frequently in the "Subsequent Events" section (59.6%) and otherwise spread across various other portions dealing with liquidity, debt, and related issues. Excluding financials and those without financial data or stock prices slightly reduces the sample to 117 firms.

3.4. Bank Relationship Data

DealScan is a common source for data on bank-firm relationships in academic research (e.g., Drucker and Puri, 2005). We supplement DealScan data with data from filings of banks taking collateral interests under the Uniform Commercial Code (UCC) rules, which potentially offer better coverage of smaller firms (Gopal and Schnabl, 2020) that tend to take PPP loans. We obtain the data as of December 2020.

We find about 270,000 lenders in the UCC data. We identify bank lenders as those with a non-missing DUNS number and a name that includes "bank," its common derivatives (e.g., "bankcorp"), abbreviations (e.g., "bnk," "bk"), and related misspellings (e.g., "bnak"). We

by name and 92.5% after using fuzzy matching algorithms. The small residual likely reflects name variations due to issues such as borrowings recorded by parents versus subsidiaries or franchiser versus franchisees. Our results are not sensitive to dropping the unmatched firms.

[10] Alternative specifications such as excluding companies that operate in an industry with 2-digit NAICS equal to 72 give similar results.

[11] Others include "Item 2.02: Results of Operations and Financial Condition" (21.3%), "Item 8.01: Other Events" (9.6%), "Item 1.02: Termination of a Material Definitive Agreement" (8.5%), "Item 1.01: Entry into a Material Definitive Agreement" (5.3%), "Item 2.03: Creation of a Direct Financial Obligation or an Obligation under an Off-Balance Sheet Arrangement of a Registrant" (5.3%), and "Item 7.01: Regulation FD Disclosure" (1.1%).

identify big banks using bank names, again filtering for variations and misspellings in names, and correct for mergers using a manual process. We then assign these classifications to UCC lenders with missing DUNS numbers using lender name. We define a firm as having a prior bank relationship if the UCC filing date is recorded in the 5 years before December 31, 2019, well before the PPP.

We also obtain from the UCC data provider the subsample of PPP recipients they could match with the universe of all firms their data hold. We could reliably match the names with the SBA PPP data. We call this dataset the UCC–SBA PPP data. Panel B of Table 1 reports the statistics for this sample. The sample covers 1.5 million borrowers (28.5% of the SBA PPP data) that obtained $298 billion in PPP loan proceeds (57.1% of the SBA PPP data). Restricting the data to corporations results in 617,749 observations, of which we eliminate 29,449 financial firms. After filtering for whether the PPP loan occurs before PPPFA, the UCC–SBA data contains 560,829 observations.

We next match the UCC bank relationship data with the public PPP dataset using the company names. The match involves 1,021 current names, approximately 1,131 former names, and over 7,300 subsidiary names of public PPP borrowers in our dataset. We find valid matches for 231 pre-PPPFA public borrowers in DealScan, 301 public borrowers in UCC, and 405 in the union. Thus, using UCC data appears to significantly expand coverage of banking relationships even in the public PPP sample. To further understand the coverage of DealScan and UCC, we examine characteristics of firms matched to both datasets, as well as of those that remain unmatched (Internet Appendix, Table IA.1). The data show that DealScan-matched firms are larger, so bringing in the UCC data incorporates many more smaller firms.

4. Early Applicants and Lender Effects

Our first analysis examines which firms gain early PPP access. From the viewpoint of firm demand, smaller and weaker firms are more distressed and constrained and they should want to access PPP funds earlier. Option to wait arguments produce similar results. Because forgiveness eligibility requires use of proceeds quickly, companies may be better off waiting for demand to recover, when PPP proceeds would be more productive. However, this option is viable only for stronger and less constrained firms, so relatively smaller and weaker firms should demand PPP proceeds sooner.

Intermediary supply effects produce the opposite predictions. Bank capacity was strained by the initial surge in PPP demand, compounding which was an aggregate shortage of PPP funds. These forces forced lenders to prioritize the clients they would push for early access.

Intermediaries had two types of incentives. One, larger and better quality firms produce greater revenues from banking relationships. Additionally, PPP fees increase in loan size while processing costs are relatively fixed, pushing banks to prioritize larger loans.[12]

The upshot is that if intermediary supply effects matter, we should find that larger firms (and loans) should be more likely to gain early access. If lender priorities vary across small and big banks, the probability of early access for larger firms should vary by bank size. Our tests are organized along these lines.

4.1. Size and Early PPP Access

We start by examining early access for public PPP recipients. Figure 2 shows the time series patterns in PPP applications. We see an initial wave before April 17, 2020, part of the early surge that depleted the initial PPP corpus of $349 billion. The next wave begins on April 27, 2020 after the PPP reopens. A brief pause occurs around May 8, 2020, the initial no-fault deadline to return funds. Loans resume thereafter and gradually taper off.

Table 3, Panel A reports data for the final sample of the 447 early and 235 late public PPP borrowers. The PPP loan amounts are greater for early applicants with mean (median) of $2.671 ($1.482) million compared to $1.982 ($0.723) million for later applicants. Larger loans are prioritized sooner, consistent with intermediary supply effects shaping the delivery of PPP funds. We note similar patterns in the larger SBA PPP dataset in Table 3, Panel B and in Figure 3, which depicts the results visually. We also see a decline in the density just above a loan amount of $2 million in PPP Round 2, consistent with investigation aversion of firms.

Table 3 also reports data on a number of financial characteristics of early versus late public PPP recipients. Early applicants are larger whether size is measured in terms of book value of assets, the market value of assets, sales, or employee counts. Early applicants also exhibit traits of better quality firms, as they are less likely to have negative book value, are more likely to pay dividends, and have greater current ratios. Once again, the findings are less consistent with firms' demand driving early access. The multivariate regressions reported in Table 4 show similar patterns.[13] Firm size is positive and significant in all specifications.

It is possible that larger firms gain early access because they can better handle PPP paperwork. Here, the evidence *within* public PPP firms is relevant. While it is plausible that small private businesses such as tiny corner stores find the PPP paperwork daunting,

[12]Larger loans are more profitable *within* buckets but there is some non-monotonicity at certain points where fees decline. For instance, simple computations show that a PPP loan of $580,000 produces less fees than one of $350,000 – although neither generates more fees than a $5 million loan.

[13]The coefficients in linear probability models are interpretable as marginal effects.

this is less plausible for publicly listed firms, who file far more complex documents to comply with periodic disclosure and audit requirements. The results for public firms indicate that intermediary supply effects shape PPP funds delivery and more generally that intermediary supply effects matter (see also Cherry, Jiang, Matvos, Piskorski, and Seru, 2021).

4.2. Size and Early PPP Access: Small versus Big Banks

We next examine whether large firm prioritization varies across small and big banks. Differences in prioritization – or the lack thereof – can speak to the client priorities of small versus big banks. The hypothesis that such prioritization can exist come from the view that the value added by big banks is access to one-stop shopping and networks, which are more relevant to larger firms. Small banks specialize in relationship-oriented lending. Recent evidence that emphasizes this viewpoint is the 2018 FDIC Small Business Lending Survey.[14] In the PPP setting, the loans are SBA guaranteed. Further, the rules are quite explicit that lenders should rely on borrower certifications and representations to submit applications. Hence soft information held by banks about borrower credit quality, one reason for housing small firm relationships in small banks (Stein, 2002) is not a consideration. Do we still see a big bank tilt towards larger firms?

Our tests need a definition of a "big bank." Our classification is based on whether a bank belongs to the top 10 banks by asset size in the U.S. The classification produces reasonable variation in bank type. The big-10 banks provide \$480 million in PPP funding in our public PPP sample while \$1.1 billion comes from smaller (non-big-10) lenders. The smaller banks provide \$802.2 million (or 71.5%) in funding in PPP Round 1 and \$280.3 million (63.6%) in funding in PPP Round 2. Relatedly, small banks seem more likely to offer early PPP access compared to big banks, a pattern seen across many specifications, suggesting that they are quicker to serve small businesses in times of need compared to big banks.

Table 5 reports the firm and loan size data for early versus late PPP borrowers cross-classified by bank type. Panel A shows that there are significant differences in both size measures between the two PPP rounds for big banks. For big banks, average early and late loan sizes are \$3.4 million and \$1.8 million, respectively, versus \$2.5 million and \$2.2 million for small banks. The early-late differences are muted for small banks. The mean asset size of big-10 bank clients is \$144.2 million for early PPP borrowers versus \$61.4 million for late PPP borrowers. For the smaller banks, the early-late size differences are muted and even reversed using this metric for size.

[14]See `https://www.fdic.gov/bank/historical/sbls/full-survey.pdf`. Other work on relationship banking includes Petersen and Rajan (1994); Berger and Udell (1995), Drucker and Puri (2005) and Bharath, Dahiya, Saunders, and Srinivasan (2007).

We present visual evidence of the size distributions for big and small banks. A leftward shift in the density of PPP customers in the later period would indicate a propensity to shift smaller clients later. Figure 4 depicts the densities of firm size for small and big banks for the early and late periods. We observe a more significant shift in the density for big banks. For big banks, the Kolmogorov-Smirnov D-statistic testing for the equality of cumulative distribution functions between early and late PPP borrowers is 0.3272 (p-value $= 0.001$). The differences are significant. For small banks, the statistic halves to 0.1527 ($p = 0.085$). We see similar patterns when looking at loan (rather than firm) size in Figure 5.

Regression results are in Table 6. We interact the natural logarithm (log) of firm assets with a bank size indicator in Panel A and log loan size in Panel B. The interaction coefficients are negative, indicating that small banks mitigate the impact of early access for large firms. Internet Appendix Table IA.2 shows that multinomial logit estimates show similar results. Small banks mitigate the propensity for large firms to get early PPP funding.

4.3. Bank Relationships

We consider the role played by bank relationships in large borrower prioritization in PPP. The bank relationship dummy variable is best interpreted as an indicator for firms that have economically meaningful bank relationships captured in the DealScan or UCC databases.

Let us start with all firms that have a recorded bank relationship with *big* banks. Early PPP access firms at big banks have a slightly greater mean book value, \$247.6 million compared to \$151.1 million for late borrowers (Table 5, Panel B). The differences are not significant. The results for PPP loan amount in Panel B are similar. Directionally, large firms go sooner but the size differences are not significant. We have one piece of evidence that relationships help alleviate earlier PPP access for large firms.

In contrast, Table 5, Panel C shows a strikingly different pattern for firms with no recorded bank relationship: early and late access firms provided with PPP funds by big banks have mean size of \$80.0 million and \$33.6 million, respectively. The difference is significant ($p = 0.003$). We find similar patterns for no-relationship borrowers at small banks, with mean firm size of \$64.3 million and \$37.7 million, for early and late PPP borrowers, respectively. The results on PPP loan amount in Panel C are similar. The sharp contrast between the no-relationship and relationship samples indicate that prior relationships help mitigate early access for large borrowers. Figure 6 and 7 show supporting evidence in graphs. The distributions of the book value of assets tilt less towards larger firms receiving PPP early when firms have prior bank relationships. The patterns are somewhat clearer in Figure 8, which plots histograms rather than densities of the probability of early PPP access.

We turn to regressions for the econometric evidence. Examine Columns 3–4 of Table 6 first, which pertain to firms with a prior bank relationship. As in Columns 1–2, the coefficients of the two size measures, firm assets (Panel A) and PPP loan amount (Panel B) in Columns 3–4 are positive but the size coefficient is significant in only one of four specifications. The more interesting evidence is based on the size-*small* bank interaction term. Here, the interaction coefficient is negative and significant. Thus, within firms with a prior banking relationship, a small bank relationship helps small firms gain early PPP access.

Let us now examine the no-relationship sample in columns 5–6 of Table 6. Large firms tend to go early, as indicated by the significant and positive size coefficient. The coefficients for the size-small bank interaction term in Columns 5–6 are now economically small and three of four coefficients are insignificant. That is, early PPP access for large firms is no longer reversed. Thus, the "concierge" treatment of larger firms is predominantly when firms do not have prior banking relationships, but it is mitigated when PPP applicants have prior banking relationships with small banks. The results are robust to using multinomial logit models (Internet Appendix, Tables IA.3 and IA.4).

4.4. The SBA PPP Dataset

We round off the analysis of relationships with evidence from the SBA PPP dataset. We note that financial characteristics such as book value are unavailable in the sample, so we use loan amount as a proxy for size. A second issue is the presence of a very large number of tiny firms. A concern this raises that they have undue influence on the results. We note this point and will present analysis attentive to this issue. The main question again is whether large firms gain early access and whether there is an attenuating effect for small banks.

It is convenient to present the visual evidence using histograms based on SBA-defined bins. We first check whether unconditionally, large firms get early access in this sample. They do. See Figure 9 for the UCC–SBA PPP sample, which, we recollect, is the universe of PPP borrowers matching with the master database of all firms maintained by the UCC database provider.[15] The next question is whether the large firm preferences vary across big and small banks. Figure 10 shows that for small banks, the histogram is relatively flat for loan amounts above the smallest bin of \$0–\$150,000 – and decreases for large loan sizes. However, the histogram slopes upward for the big banks. Thus, even in the SBA PPP sample, big, but not small banks, appear to prioritize big firms for early access.[16] Panels C through F report the data classified by bank relationships. We do not find it easy to tell any

[15]The results for the full SBA sample in Internet Appendix Figure IA.1 are similar.

[16]The results are robust to shrinking small bank capacity in a manner that creates equivalence between the proportion of PPP clients that big and small banks serve early. There results are available upon request.

differences between big and small banks in the figures. We turn to the statistical evidence.

For the basic descriptive statistics, we revert to Panel B, Table 3. We have 274,764 early and 286,065 late PPP applicants in the UCC–SBA sample. Size is again positively correlated with early access. For example, in this sample, the mean (median) PPP loan size for early applicants is \$277,680 (\$109,913), whereas it is \$128,396 (\$49,877) for late applicants. The results are similar if we use the number of jobs supported by the PPP, which we tread here with caution given press reports that there may be errors in jobs reporting.[17]

We turn to regressions in Table 7 using a structure parallel to that in Table 6. Early access is the dependent variable. Of interest are the coefficients for PPP loan amount and its interaction with the big-small bank indicator. Controls in the SBA PPP dataset include granular NAICS-6 industry and zip code level geography fixed effects, the fields made available in the release.

The results have an interesting feature that we address after discussing the main results. In all specifications in Table 7, the coefficient for the size is positive. Thus, size is positively related to early access and consistent with intermediary supply effects shaping PPP supply. Turn to specifications (2) and (3) in Table 7. Specification (2) shows that the coefficient for the size-small bank interactive term is negative. This is the by-now familiar result that small banks help undo the large firm prioritization, now obtained for the broad PPP sample. In the no-relationship sample, the coefficient is now *positive* and significant. Thus, absent prior banking relationships, small banks preference larger loan amounts even more. The results based on multinomial logit models are qualitatively similar (Internet Appendix, Table IA.5).

An interesting feature of the results in Table 7 is the *positive* coefficient for the small bank-firm size interaction in specification (1) that does not condition on bank relationships. This sign, which indicates that small banks prioritize large firms *more* than big banks, is exactly the opposite of what we find for the public sample in Table 6. In a statistical sense, any sign is possible because the overall specification should average the positive and negative coefficients in specifications (2) and (3). However, the economics are interesting and reflect the point made in opening this section: the preponderant presence of very tiny firms. We investigate this issue formally.

In the aggregate PPP dataset, loans in the lowest SBA bins of below \$150,000 and between \$0 and \$350,000 account for 69.7% and 86.1% of the observations, respectively. There is a very large number of tiny "microloans" in the SBA data set. To what extent do they drive the results, especially the positive firm size-small bank interaction coefficient in the first

[17]E.g., see "Faulty data collection raises questions about Trump's claims on PPP program," Washington Post, July 14, 2020 at https://www.washingtonpost.com/business/2020/07/14/ppp-job-claims-sba. Note also that the SBA reporting may vary because of PPP requirements (e.g., foreign employees) or because not all firm's affiliates are able to apply.

specification in Table 7? As one test, we redo the regressions replacing loan amounts with bin indicators based on SBA loan buckets. We find that the anomalous positive interaction term is *only* in the smallest bucket. Another approach drawn from the asset pricing literature is to report "value weighted" results based on weighted least squares that assigns greater weights for larger loans. The coefficient for the size-small bank interaction reverses from 0.0262 to -0.0410 (p-value <0.001), the familiar result that small banks help undo the prioritization of large firms for early PPP access. These results are available upon request.[18]

Finally, we examine whether, within the universe of bank relationships, applying through relationship banks helps early access. Table 8 reports the evidence. Specification (1) shows the baseline result. The coefficient for applying through a relationship bank is positive, so applying through a relationship bank enables early access. Specification (2) examines the role of a prior *small* bank relationship. Once again, having a small bank relationship appears to help with early PPP access. Finally, in specification (3), we interact the small bank relationship with applying through a relationship bank. The positive sign indicates that the effects of applying through a relationship bank are more pronounced when the bank is small and the borrower has a prior relationship with the small bank.

To summarize the results, the PPP is an interesting natural experiment in which banks face a sudden and unexpected shock in which they must prioritize their clients. Given government guarantees of PPP loan repayment, traditional soft information considerations are not relevant in this setting. Larger clients appear to gain beneficial access to PPP funds sooner, an effect that is attenuated in small banks. The more even treatment of small clients is perhaps one reason why small firms bank with small banks, as banking with larger banks could lead the small firms into facing a "small fish in a big pond" effect. The relative prioritization of small businesses offers a different rationale for why small firms domicile their bank relationships with small banks worthy of more attention by academicians and regulators alike.

5. PPP Uptake

Besides the intermediaries involved in piping PPP supply to borrowers, a second force that drives PPP uptake comes from the concerns of small firms that are the program's targets. We open with an analysis of PPP uptake and show that it has positive average valuation effects, a metric of the program treatment effects. We then uncover a curious PPP

[18]The results are consistent with the view that small banks push small firms when the stake is meaningful, perhaps because of the greater option value from better chances of firms surviving and becoming economically consequential in the longer term.

"funding hesitancy," characterize related valuation effects, and explore the possible sources of this hesitancy exploiting the structural features of the program. This analysis focuses on public PPP recipients, as we observe the event of PPP return only for this sample. Control firms are small non-applicants identified in Section 3.

5.1. *Characteristics of PPP Applicants*

To understand PPP uptake, we begin by describing the types of listed firms that apply for PPP. Table 9 shows that the median (mean) PPP loan amount equals \$1.1 (\$2.4) million, representing 4.41% (7.30%) of the book value of assets and 3.52% (10.98%) of the market value of equity, respectively. The median (mean) ratio of the loan amount to cash and equivalents winsorized at 100% equals 26.9% (43.2%). Thus, PPP loans are economically meaningful relative to the liquidity on hand for our sample firms.

5.1.1. *Industry*

The SBA uses NAICS industry classifications in its lending operations. We drop firms with NAICS-2 equal to 99, special purpose acquisition firms, 79 PPP applicants from the financial sector, combining those with fewer than 20 PPP applicants into one bucket.[19] Figure 11, Panel A shows that the percentage of applicants varies substantially across sectors, ranging from lows of 4% to 5% in NAICS-2 = 22 and 48 to upwards of 50% in NAICS-2 = 33, 49, 54, and 56. The probability peaks at 70% for NAICS-2 = 72, the "accommodation and food services" sector that includes chain restaurants such as Denny's and Shake Shack relying on franchising as a business model. We include these firms in the main analysis, but excluding them does not alter our main conclusions.

For the regressions, we construct a suite of industry fixed effects with two considerations in mind. One, we attempt to construct industry variables of economic interest. The second is the familiar practical consideration, creating industry clusters that are populated sufficiently to result in estimable regressions. Internet Appendix Section IA.B describes the four industry clusters and shows that they capture substantial variation in application probabilities (see Figure 11, Panel B).

5.1.2. *Financial Characteristics of PPP Applicants*

Table 9 reports characteristics of PPP loan applicants as well as those of control non-applicants. The p-values are based on Wilcoxon rank-sum tests as many variables are skewed.

[19]The consolidated sectors have 67 firms from NAICS-2 = 11, 23, 44, 45, 52, 61, 71, and 81.

Panel A of Table 9 shows that PPP applicants are small. The mean (median) market value of equity of applicants, \$110.9 million (\$35.9 million), places the firms in the smallest Fama-French size decile. Applicants are smaller than non-applicants, whose mean (median) market value equals \$484.7 million (\$118.7 million). Other size metrics such as book value, sales, and the number of employees show the same pattern.[20]

PPP applicants appear to have less liquidity and less financing access relative to the small firm pool. Their cash and current ratios are lower and are highly unlikely to have credit ratings, which signals credit access (Faulkender and Petersen, 2006). Over 70% of the PPP applicants fall into the top quartile of constrained firms according to the Whited and Wu (2006) (WW) or the Hadlock and Pierce (2010) (SA) financial constraints indexes. PPP applicants also have greater distress risk. Applicants have low interest coverage ratios: more than three-quarters of them cannot cover interest 2.5 times, a benchmark for large investment grade companies. Over 68% of PPP applicants have Altman (1968) Z-scores below 1.81, a benchmark for high default risk. PPP applicants have lower distance to default (Bharath and Shumway, 2008; Duan, Wang, et al., 2012), lower nominal share prices, and 75.2% of them are penny stocks, an indicator of mortality.[21]

We note that the patterns are prior to the pandemic – and not caused by it. Thus, PPP applicants are smaller, weaker, more constrained, and have less liquidity than typical small firms *before* the pandemic. Moreover, these firms do not seem to have done better in the pandemic. Figure 12 shows that PPP applicants have lower average cumulative buy-and-hold abnormal returns (BHARs) from January 1, 2020 to March 23, 2020, the day before the passage of the CARES Act. Applicants do not do better in terms of returns from February 3, 2020 to March 23, 2020, the Covid period defined in Fahlenbrach et al. (2020) or in returns on March 24, 2020, when there was news on the imminent passage of the CARES Act.

Table 10 reports estimates of several regressions that explain the characteristics of PPP applicants relative to control firms. The return variables are interacted with a penny stock dummy variable to account for noise in price data in the latter. The regression results indicate that applicants are smaller, older, slower growing, and have less liquidity. The data paint a clear picture of the types of firms that apply for PPP. The applicants are typical of small firms in some respects and where there are differences, the PPP applicants appear to be weaker: smaller, less liquid, more constrained, and with greater distress risk. Additional tables employing indicators of constraints and distress, not reported here, give similar results.

[20] We note here that the results are conservative. The COMPUSTAT-disclosed number of employees for PPP firms is sometimes more than 500. For example, PPP eligibility for hotels is based on employees in an establishment, but COMPUSTAT reports the total employment count.

[21] See Seguin and Smoller (1997) and the SEC guidance on penny stocks, available at `https://www.sec.gov/fast-answers/answerspennyhtm.html`, which argues that these stocks are risky.

5.2. *PPP Application Announcement Effects*

We next examine the stock market valuation effects related to PPP. Figure 13 shows CARs (cumulative abnormal returns) for [-5, 5] where [0] denotes the filing date. The average CAR is over 4% in the time interval [-5, 1], much of it in [-2, 1]. From Panel B, the results are similar for both market adjusted or market model abnormal returns.

Table 11 uses a narrow [-1, +1] window around the filing date to estimate PPP uptake valuation effects. The estimates regress daily abnormal returns (using market-adjusted or market model returns) from January 1, 2020 until the event date plus one day. The independent variables of interest are the three dummy variables representing the filing date plus or minus one day. Using a regression sample *within* the pandemic period addresses the point in prior research that pandemic period returns are unusual. We include firm fixed effects, which absorb firm-level heterogeneity within the pandemic period. Finally, we account for the possible bunching of PPP applications in waves (Figure 2) by clustering standard errors by calendar dates.

We report three estimates, one for all PPP applicants, another one for those reporting PPP in 8-Ks, and finally, a sample that excludes penny stocks. For the full sample, Panel A of Table 11 shows that the PPP abnormal returns are about 1.1% and accrue on day [-1]. The estimates increase to about 1.6% for firms announcing PPP through 8-Ks. This increase is not surprising given that 10-Qs or 10-Ks contain other information and are thus less precise in picking up PPP information. See also Heitz, Narayanamoorthy, and Zekhnini (2020). Excluding penny stocks produces somewhat greater coefficients with no material impact on standard errors (Panel C). The announcement effects are somewhat greater for the subset of larger applicants. Overall, there is little evidence that taking PPP harms shareholders. In fact, PPP uptake appears to increase share prices.

5.3. *Partial Anticipation and Treatment Effects*

We discuss unadjusted treatment effects first. Using announcement effects and the pre-announcement value of PPP applicants, we find that the average change in the dollar market value of a PPP applicant is \$1.57 million (after 1% winsorization to account for outliers). Across all the 555 PPP borrowers for which we have the relevant data, the total change in value is \$871.61 million. As the total PPP loan amount for these firms equals \$1.590 billion, the PPP bang for the buck equals \$871.61 million $\div$ \$1.590 billion $=$ 0.548. The 417 penny stocks in our sample take \$937.94 million in PPP loans and experience an increase in market value of \$342.44 million, giving a bang for the buck of just 0.365. The non-penny stocks, the stronger firms, gain \$522.95 million and take \$651.84 million, giving a bang for the buck of about 0.802. Thus, the bang for the PPP buck is greater for the larger and stronger firms.

We adjust for partial anticipation next. Valuation changes on the event date are less than the actual event effect if an event is partially anticipated, as anticipations bake potential treatment effects into the pre-announcement share prices. We adjust for anticipation by scaling up the announcement returns by a factor related to the probability of PPP application (Acharya, 1988; Eckbo, Maksimovic, and Williams, 1990; Prabhala, 1997).

Suppose q_f is the probability assessed by the market that firm f applies for a PPP loan. Let the benefit of the PPP be B. On the date the market learns that firm f has applied for PPP funds, the change in its value, say D, equals $(1 - q_f)\,B$. Thus, the actual benefit B equals $\frac{D}{1-q_f}$ and the aggregate across all firms is $\sum_f \frac{D}{1-q_f}$, where $0 \leq q_f \leq 1$. We obtain estimates of q_f, the ex-ante probability of applying for PPP, from Table 10.

For the 533 PPP borrowers with the relevant data, the anticipation-corrected treatment effect of the PPP program equals \$1.411 billion, 91.2% of the aggregate PPP loan amount of \$1.548 billion. The bang for the buck is thus 0.912.[22] For penny stocks, the bang for the buck is 0.817, reflecting gains of \$742.20 million versus loan amounts of \$908.27 million. For non-penny stocks, it is 1.046, with shareholder gains and PPP loan amounts of \$669.08 million and \$639.40 million. As before, the larger, stronger PPP applicants produce a greater bang for the PPP buck.

5.4. *Economics of the Estimates*

How useful are the stock market data in understanding the PPP program impact? While impact assessment is not our focus, we comment briefly on this issue. In our view, the stock market valuation effects are useful as we have reasonably accurate times (news release dates) when share prices impound the PPP impact. On the other hand, share prices may not be the primary impact metric, which may be outcomes such as jobs or wages. But shareholder value is not entirely without use. The PPP was designed to keep enterprises running and is more impactful when business owners experience its positive effects. Additionally, the number of public PPP firms is small. Thus, any analysis of share prices, however accurately they pin down impact, does not subsume the need for alternative impact assessment studies. Our study simply adds one more data point and a different lens for this assessment.

Some other points are worth mentioning in this context. The PPP is announced alongside other aid packages as part of the \$2 trillion CARES Act bill. The other pieces of the bill – and other local pandemic and economic mitigation measures – can be confounders in

[22] We note that one large borrower, AutoNation, takes \$77 million in PPP loans and has about 10 times the amount as shareholder gain. We thus winsorize changes in value at the 1^{st} and 99^{th} percentiles to ensure that outliers like AutoNation do not drive the average treatment effects.

interpreting PPP effects. Our experiment design mitigates such concerns. In our study, stock prices reflect impact on event dates, which are staggered across firms and spaced away from the CARES Act announcement. Moreover, the totality of the CARES package is perhaps reflected in (and thus contaminates) the aggregate stock market return but the market return is stripped out when we compute abnormal returns.[23]

A final point is related to real-time economic tracking, a focus of the economics literature particularly in the wake of the pandemic (see Chetty et al., 2020), but also in other areas such as nowcasting macroeconomic data. The stock market responses are in fact a real-time assessment of the program effects that incorporate information known to market about the PPP application and its assessment of PPP effects. We do not advocate extrapolating our estimates of treatment effects to the entire $525 billion as the non-public firms have simply no analog in the public space, e.g., private schools or not-for-profit organizations. In our view, the takeaway is that even in public firms, the valuation effects are positive but the bang for the buck is small and concentrates in the larger and stronger subset of firms.

6. Funding Hesitancy

We turn to tests of funding hesitancy. As discussed in Section 1, several firms that obtained PPP loans returned the funds within a short period of time before using the funds. We characterize the decision to return PPP funding, examine related valuation effects, and assess evidence for the role played by government investigation threats in the decision to return PPP funds.

6.1. Returners versus Retainers

Table 12 reports the characteristics of 117 public firms that returned PPP loans – henceforth "returners." Alongside, we report the characteristics of the 565 public PPP recipients firms that did not return PPP funds – henceforth "retainers." The mean (median) loan amount for PPP returners equals $4.43 ($3.33) million compared to $2.02 ($0.96) million for retainers. Firms that return PPP money have applied for larger loan amounts. As we will see shortly, returners also appear to be larger by other metrics and somewhat financially stronger.

The mean (median) book value of assets for the returners equals $288.4 ($86.0) million compared to $71.4 ($27.7) million for the retainers. Table 12 shows that the difference is

[23] The broad market-wide effects of PPP are perhaps best reflected in the market's positive reaction (+9.38%) to the PPP on March 24, 2020, but this is not the impact of PPP alone as the program is embedded in the larger CARES package.

significant. We see similar differences in other size characteristics including market capitalization, sales, and the number of employees. Returners are less likely to have negative book value, have higher Tobin's Q but lower sales growth, and are more likely to pay dividends (24.3% versus 12.4% for retainers). Returners have better liquidity with higher current ratios, cash balances, and are more likely to be rated (6.0% versus 1.9% for retainers) although access to public debt is overall low, as typical for small firms. Returners are also less financially constrained per the Whited-Wu and the Hadlock-Pierce SA indexes, have greater distances to default, higher Altman Z scores, and are less likely to be penny stocks compared to retainers. Returners are clearly stronger than retainers.

We also examine industry patterns (Figure 14). Around 22.5% of health sector firms return PPP funds compared to 15.1% of non-health firms. In contrast, only 10.7% of high-tech firms return PPP funds compared to 18.4% of firms in non-high-tech industries. While both industries faced better prospects in the pandemic, the health firms have greater regulatory interactions, which may explain why these firms are less likely to keep PPP funds and face the prospect of a negative investigation. Only 11.4% of the firms in industries impacted by Covid return PPP funds compared to 18.3% in non-Covid industries. Likewise, only 12.5% of machinery industry firms return PPP funds compared to 17.3% of firms that are not in the machinery sector. Thus, firms with greater demand for funds and those more prone to distress from illiquidity are less likely to return funds.

We do not find evidence that returners benefit less from PPP stimulus (Figure 15 and Table 12). The mean (median) stimulus day return of PPP returners equals 7.0% (6.5%) compared to 5.2% (3.6%) for retainers. The data show that the Covid period returns and the PPP loan announcement effects are similar for the two samples. Returners have a higher PPP application bang for the buck than do the retainers. Little in these patterns suggests that firms that return PPP funds are the ones that have benefitted less from PPP.

6.2. Regression Evidence

Table 13 reports estimates of regressions that model the decision to return PPP loans. In the sample are 543 PPP firms with sufficient data. The role of firm size is notable. Large firms are more likely to return PPP funds. A one standard deviation increase in the natural logarithm of assets increases the probability of returning the PPP loan by at least 9.05 pp, or by 52.74% relative to the unconditional mean. This result also holds for firms with at least $50 million in market capitalization. Penny stock firms are less likely to return PPP funds. As discussed earlier, research (e.g., Seguin and Smoller, 1997) suggests that penny stocks face greater failure hazard, and given their classification as speculative investments, face greater hurdles in capital raising. We find that these firms are more likely to retain PPP funds.

Specification 3 includes stock return data. We find that firms with *better* Covid period returns tend to return PPP funds. In Internet Appendix Tables IA.6 and IA.7, we find that less constrained and low bankruptcy firms are more likely to return PPP funds. Collectively, these findings add to the basic point that returners are more likely to be the better quality applicants for PPP – even before the pandemic – concentrating PPP uptake among the weaker firms.

6.3. PPP Return Announcement Effects

We display the cumulative abnormal returns (CARs) associated with PPP return starting from date $t = -5$, where $t = 0$ denotes the filing date of the disclosing 8-K. Figure 16 shows that the announcement effects are positive for both the market-adjusted and the market model abnormal returns. In Figure 17, we find that PPP return dates spike in early May 2020, when the SBA clarified that firms returning funds early would not be audited.

Table 14 reports the estimates of a fixed effects regression of the abnormal return on date dummy variables that are non-zero in [-1, +1] where [0] is the filing date. The sample includes returns in [-60, +1]. We cluster standard errors by calendar date. The announcement effect is about +3% regardless of the specification.[24] We consider treatment effects akin to those for announcement effects. The average change in value is \$11.74 million, with the total of \$1.256 billion across all 107 borrowers for which we can compute this statistic.[25] The amount of the loan returned is \$538.87 million, producing a bang for the buck estimate of about 2. If we add the loan amount returned, \$538.87 million, to the dollar announcement effect, essentially assuming that the loan amount was a wealth transfer, wealth effect of returning PPP is \$1.795 billion.

As before, we can correct announcement effects for partial anticipation by scaling them for the portion impounded in the pre-announcement share price, which is $(1 - q)$ where q is the probability that the funds are returned. Doing so using the probability model estimated in Table 13 shows that anticipation-corrected net gain is \$2.148 billion across 105 PPP returners. Returning \$530.64 million should have resulted in losses of \$530.64 million to the returners but instead this turns into a gain of \$2.148 million, or about 10.5% of firm value (before PPP return announcement).

[24] The results are robust to excluding a small number of firms (about a half-dozen) who indicate in their 8-K disclosures that their performance has improved.

[25] We winsorize changes in value at the 1^{st} and 99^{th} percentiles to account for outliers such as AutoNation.

6.4. More Evidence on Indirect Costs of PPP

The fact that firms return PPP although it is bargain financing – and that markets react positively to it – suggests that there are indirect costs of taking PPP. The release from these costs is realized when PPP is returned and is valued by markets. We next consider tests that can speak to the nature of these costs, specifically those arising out of government investigation. Before these tests, we consider some other explanations for PPP return.

One possibility is that returners have alternative sources of funds. Equity financing is one possible source but equity issuance traditionally sends a negative signal to the market. A better candidate is bank lending, whose announcements trigger positive announcement effects (James, 1987; Lummer and McConnell, 1989; Billett, Flannery, and Garfinkel, 1995; Chen, Ho, and Liu, 2019). This interpretation, if correct, reinforces our point concerning indirect costs. If firms prefer more expensive bank capital over far cheaper PPP funding, it suggests that they see positive value in being subject to scrutiny by private capital providers but the same scrutiny by the government has negative value.

Another explanation is signaling. According to this hypothesis, firms return PPP funds to signal improvements in firm fundamentals otherwise unobserved by the market. We have reservations about this explanation. One issue is that the $2 million discontinuity, which we will turn to shortly, is not relevant for signaling. Another is the evidence on announcement effects by firm size. Signaling should be stronger when less anticipated, that is, for smaller and worse-quality firms. We do not find this in the data. We leave more tests of signaling for future work, not necessarily mutually exclusive from the ones we examine.

6.4.1. Loan Amount and PPP Return

If government investigations are more likely for large PPP loans, the probability of returning PPP funds should increase in PPP loan size. We note that audit pronouncements were released at various points of time in late April to May.[26] Thus, investigation concerns are less likely to have informed *applications* that occurred before but could drive the decision to return PPP.

Figure 18 shows that the probability of returning PPP funds is greater for larger loan amounts. We confirm the positive relation between PPP loan return and loan size in regression analysis in Table 15 (Column 1). We find that a one standard deviation increase in the

[26] E.g., see "Joint Statement by Secretary Steven T. Mnuchin and Administrator Jovita Carranza on the Review Procedure for Paycheck Protection Program Loans," SBA, April 28, 2020 at https://www.sba.gov/article/2020/apr/28/joint-statement-secretary-steven-t-mnuchin-administrator-jovita-carranza-review-procedure-paycheck and "PPP Changes Trip Up Small Businesses," Wall Street Journal, May 12, 2020 at https://www.wsj.com/articles/paycheck-protection-program-changes-trip-up-small-businesses-11589288403.

natural logarithm of PPP loan amount increases the probability of returning the loan by 10.36 pp, or by 60.37% relative to the unconditional mean. We examine other tests next.

6.4.2. $2 Million Discontinuity: PPP Return

A second test concerns a $2 million loan amount threshold for loan audits. The interim final rule issued by SBA in the Federal Register on June 1, 2020 says that all loans are subject to audit. However, both the Treasury and the SBA have indicated that firms with loans less than $2 million will be presumed to have applied in good faith.[27] If this is relevant, firms just above the $2 million threshold experience more threats relating to PPP investigation than those below.

We first examine univariate statistics around the $2 million threshold. The sample odds of returning PPP funds are 9% for loan amounts of $1.5–$2 million but more than double to 24% for loan amounts between $2–$2.5 million (Figure 18). Relatedly, 9.50% of the 442 firms with loan amounts less than $2 million returned PPP funds, while 31.2% of the 237 firms with loan amounts more than $2 million did so. The discontinuity in PPP return probability is clearly visible in Figure 19 that superposes the histogram for applying for PPP on the histogram for returning PPP. The discontinuity in PPP returns is quite stark here.

We turn to discontinuity designs around the $2 million loan amount threshold. One issue in this type of analysis is statistical power. Regression discontinuity designs fit high order polynomials to the running treatment variable and then check for discontinuities. Our public PPP sample is relatively small to filter out the non-linear curvatures present under a hypothetical null, with the additional difficulty of having a 1/0 outcome variable for returns and in local designs that use even smaller subsamples centered around the $2 million threshold. We choose to include all observations in a global design. This approach brings in more observations but ones that are more distant from the threshold are possibly less informative of considerations around the $2 million threshold. We have no easy answer to this tradeoff but present the evidence for what it is worth and turn to other evidence in larger samples thereafter.

Table 15 gives the regression results. The coefficient for the threshold indicator is the marginal effect of borrowing above the discontinuity threshold beyond the effect of PPP loan size. In the baseline model, this threshold indicator coefficient is positive and significant. The probability of returning the loan increases by 8.85% when firms borrow $2 million and above (Column 2). The coefficient remains positive but with reduced significance when we

[27] E.g., see "SBA Clarifies Certification Requirements Today For Paycheck Protection Program Borrowers," Forbes, May 13, 2020 at https://www.forbes.com/sites/juliejason/2020/05/13/sba-clarifies-certification-requirements-today-for--paycheck-protection-program-borrowers.

incorporate the full set of controls (Column 3).

6.4.3. $2 Million Discontinuity: Loan Application

We exploit another PPP design feature that creates a different type of discontinuity around the $2 million cutoff but speaks to the government investigation concerns in the larger SBA PPP sample. The SBA announced that PPP funds returned before May 18, 2020 would be presumed to have been made in good faith and thus not subject to audit.[28] Thus, if investigation threats are of concern, we should see that PPP *applications* after May 18, 2020 should tail off just above the $2 million threshold relative to just below.[29]

Figure 20 shows the histogram for SBA loan application amounts before and after May 18, 2020. A discontinuity appears in the PPP application density just above the $2 million cutoff after the PPP return deadline. Before May 18, 2020, applications for loan amounts between $1.5–$2.5 million comprise 66.56% of applications for $1.5–$2 million. After May 18, 2020, 90.48% of all applications for loan amounts between $1.5–$2.5 million are applications for $1.5–$2 million. This result suggests that investigation aversion is a part of the PPP funding hesitancy we find. The threat of audit appears to have deterred some firms from applying for PPP – or pushed them to apply for amounts below $2 million.[30]

6.4.4. Indicative UK Evidence

We next consider some evidence from the UK. Here, the government program to aid businesses in the wake of Covid took the form of a business rates relief program, equivalent to relief on property taxes. This program also saw "PPP-like" returns of funds. An important difference is that in contrast to the U.S., firms in the U.K. returned government aid due to public pressure that was not accompanied by any explicit or implicit threat of government investigation.[31] Thus, share price responses to returns should be free of concerns about government investigations and reflect, e.g., losses from access to Covid-19 related relief.

We gather data on U.K. business rates relief returners from press reports. The subset we identified from press reports includes large retailers: Tesco, Sainsbury's, Morrison's, Asda,

[28] E.g., see "PPP Loan Rules Relaxed By SBA For Loans Under $2,000,000 – Uncertainty Still Abounds For Many," Forbes, May 14, 2020 at https://www.forbes.com/sites/alangassman/2020/05/14/ppp-loan-rules-relaxed-by-sba-for-loans-under-2000000uncertainty-still-abounds-for-many.

[29] The before-after design mitigates fee discontinuity related explanations – the fees did not change but the application behavior did. Relatedly, we don't see a discontinuity for the $350,000 loan amount cutoff that also presents a fee discontinuity.

[30] The public sample is rather small for a before-after May 18, 2020 design. However, Figure 3 shows a decline in the density of PPP applications by public firms above the $2 million cutoff in PPP Round 2.

[31] See, e.g., *£1.8Bn-Plus in Covid Rates Relief to Be Handed Back as B&M Joins List*, The Guardian, December 3, 2020 and *B&Q Owner Kingfisher to Repay £130M of Covid Business Rates Relief*, The Guardian, December 7, 2020.

B&M, Pets at Home, and Whole Foods. The announcement effects for the subset with returns is *negative*, and range from -2.05% to -11.08%. One interesting case is that of the retailer Marks and Spencer, which announced that it would not shy away from the business rates relief. Upon this announcement, the firm experienced +9.02% abnormal return. The UK evidence suggests that returning subsidies unrelated to scrutiny avoidance results in negative announcement effects. In the U.S., we see positive announcement effects when firms return subsidized funding, supporting the investigation-avoidance interpretation of our U.S. PPP return results. As additional evidence, Internet Appendix Section IA.C gives extracts from company reports showing concerns about scrutiny motivating PPP returns.

7. Conclusion

The Paycheck Protection Program (PPP), a fiscal stimulus program in the U.S., aims to help small businesses suffering from the economic fallout of the Covid-19 pandemic. At $669 billion in fiscal commitments, the PPP is a significant portion of the $2 trillion CARES Act package intended to help the country through the deep, sudden, and widespread economic contraction and job losses from the Covid-19 pandemic.

The PPP is a significant shock in the supply of financing to small businesses. It provides extraordinarily cheap financing to small businesses that are highly constrained even in normal times. We use this shock to examine two questions. One is about using financial intermediaries to pipe the funding supply, which highlights the supply decisions of small and big banks under situations of extreme constraints. The other concerns the "funding hesitancy," or the apparent reluctance on the part of small businesses to receive government funding.

The first question concerns PPP funding delivery through the banking system. Banks are the dominant types of financial institutions in most countries and have widespread branch networks with extensive reach. Thus, they are logical entities to use to deliver funding to important sectors.[32]The need to get credit to important sectors is especially relevant in difficult times. But banks have their own incentives which can shape the delivery system. Our findings suggest that there are intermediary supply effects, that is, bank financial intermediaries shape the supply of PPP financing. Our evidence suggests that larger firms are likely to gain early access but the pro-large firm effects are attenuated in small banks and when firms have prior banking relationships.

[32]For example, in Germany, a bank-based system, German banks tried to develop the German VC market (Da Rin, Hellmann, and Puri, 2013). In India, banks are given quotas for priority sector lending, in the hope of getting credit to underserved, critical sectors and jumpstarting their growth (Banerjee and Duflo, 2014).

The finding is interesting in light of the large literature in banking suggesting that small firms benefit from pairing up with small banks. The literature lends empirical support to this proposition, and theoretical justification. Stein (2002) lays out a theory that explains this matching based on soft information. A number of papers have examined Stein (2002)'s theory, using different experiment designs, starting with Berger et al. (2005) who finds supportive evidence of small banks being better able to collect and act on soft information than large banks. But the literature has not converged on other additional reasons for small firm-small bank pairing. Our evidence suggests a new rationale for small firm-small bank pairing through evidence in which there is a large shock but credit risk – thus private information and soft information – is not at play given repayment guarantees.

We find that absent relationships both small and large banks prioritize large firms. This is consistent with underlying incentives since, if capacity constraints bind so that banks can process only a fixed amount of loan applications, banks make more fees by processing larger loans. Interestingly however, this prioritization flips when prior banking relationships are taken into account. Small banks prioritize small firms with prior bank relationships but we do not see similar prioritization by large banks. In times of shock and capacity constraints, small banks are more likely to prioritize small firm relationships. Given that PPP loans are guaranteed by the government, and there is no private or soft information involved our results suggest a new rationale for the benefits of pairing of small firms with small banks.

With its extraordinarily inexpensive financing terms, the PPP is also a very positive shock in financing supply to small businesses. Taking PPP has positive announcement effects, consistent with beneficial program impact for our small universe of public firms. Nevertheless, we detect a "funding hesitancy," some reluctance on the part of firms to take up PPP. Perhaps the most stark evidence of this hesitancy is that several public firms that bring up the bottom in terms of financial constraints indexes, manage to qualify for, apply for, and take PPP funds – yet return the money without using it as the program unfolds and the threat of government investigation begins to loom large. Interestingly, returning the PPP funds results in positive announcement effects, indicating that both firms – by revealed preference, giving up cheap funding – and markets value the release from PPP.

The findings suggest that taking PPP funds imposes significant indirect costs on participants. The costs appear to be related to the possibility of ex-post investigations of PPP recipients. Of concern are the subjectivity in the audit process, the broad powers of the government to seek remedies, and especially an openly adversarial stance towards public firms articulated in its pronouncements. It does not seem surprising that firms choose to turn away from PPP funding. Firms that are stronger before the pandemic tend to do so, concentrating PPP funds among the financially weaker applicants. From a policy viewpoint, our findings suggest that when taxpayer funding is involved, policymakers should focus on both objective standards for program eligibility and also specify with similar objectivity the conduct of the ex-post audits concerning funds use. For instance, delineating safe harbors to circumscribe litigation, a standard practice in securities law since the 1930s, may be an appropriate tool in designing government aid programs.

Understanding the intermediary supply effects, market responses to PPP funding, and funding hesitancy can help design better policies for small businesses. We hope that our findings also shed light on and help move forward research on the nature of firm-bank relationships, especially for small firms and small banks.

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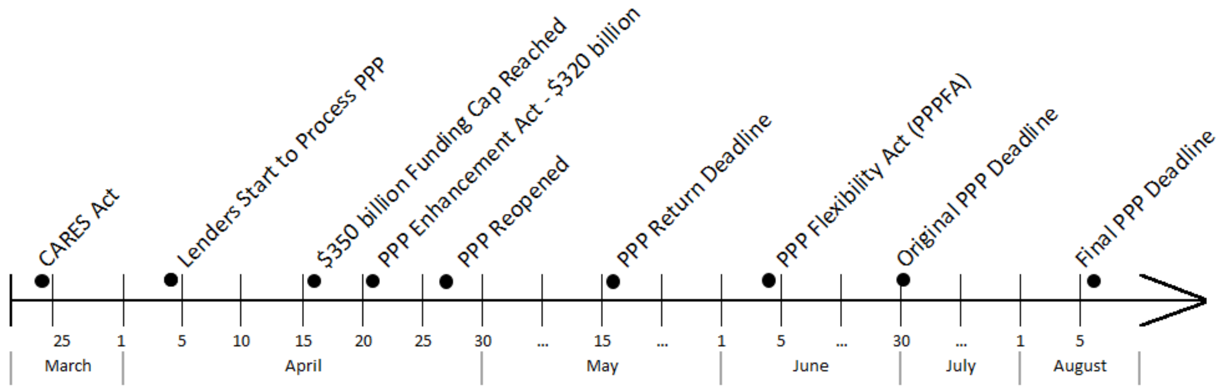

Figure 1. PPP timeline. This figure illustrates the timeline and key milestones of the Paycheck Protection Program (PPP).

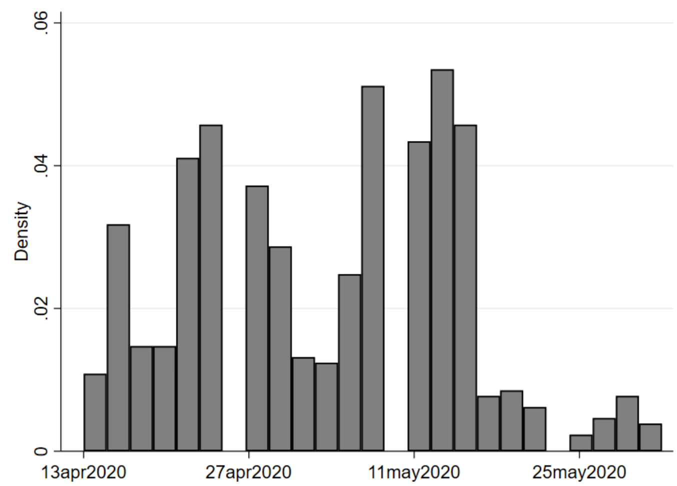

Figure 2. Density of PPP loan grant announcement dates. This figure plots the density of announcement dates for PPP loan grant announcements by public PPP borrowers.

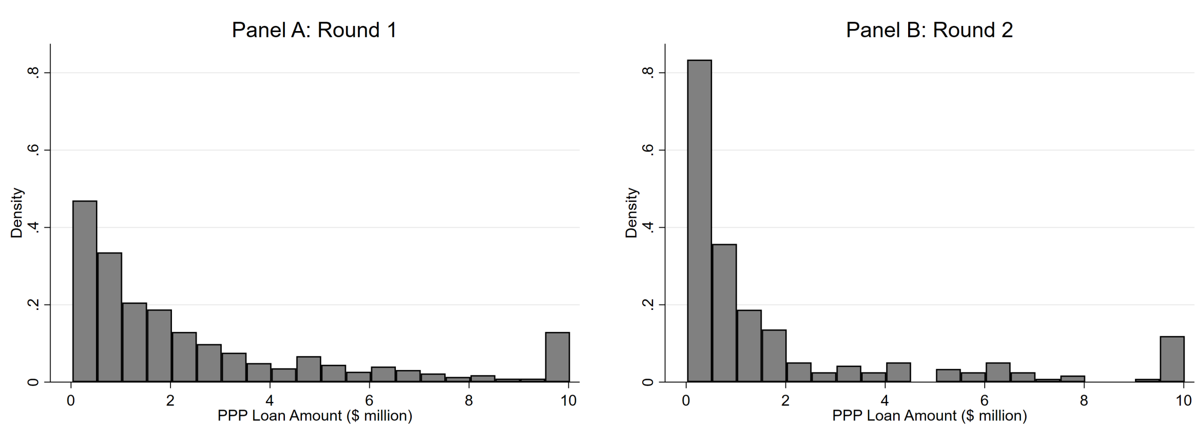

Figure 3. PPP loan size by PPP Round. This figure plots the density of PPP loan size for PPP Round 1 (before April 17, 2020) versus PPP Round 2 (after April 26, 2020) for public PPP borrowers. We set PPP loan size to $10M for loans above $10M, for the ease of exposition.

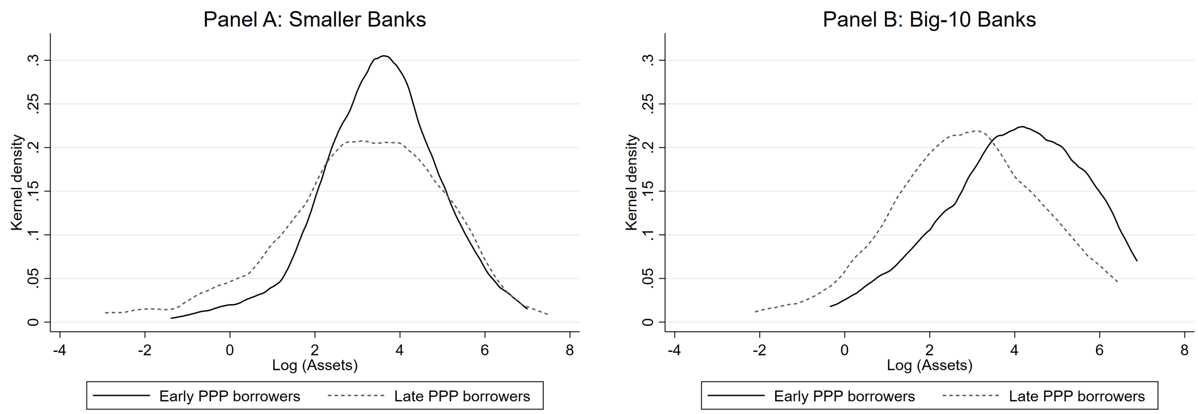

Figure 4. Early PPP access and firm assets: small versus big banks. This figure plots kernel densities of the natural logarithm of firm's assets for early versus late public PPP borrowers. Panel A reports the results for smaller (non-big-10) banks. Panel B reports the results for big-10 banks. *Log (Assets)* is winsorized at the 1^{st} and the 99^{th} percentiles.

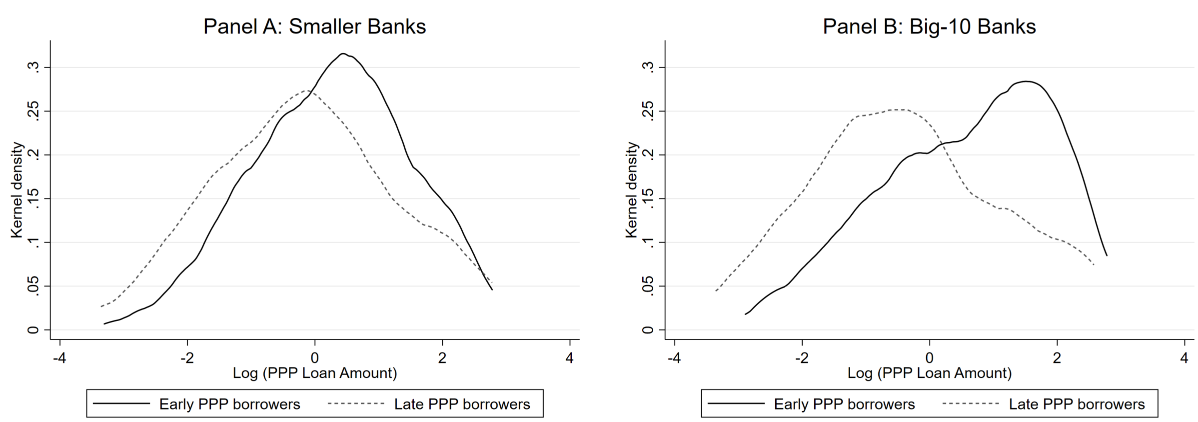

Figure 5. Early PPP access and PPP loan size: small versus big banks. This figure plots kernel densities of the natural logarithm of PPP loan amount for early versus late public PPP borrowers. Panel A reports the results for smaller (non-big-10) banks. Panel B reports the results for big-10 banks. *Log (PPP Loan Amount)* is winsorized at the 1^{st} and the 99^{th} percentiles.

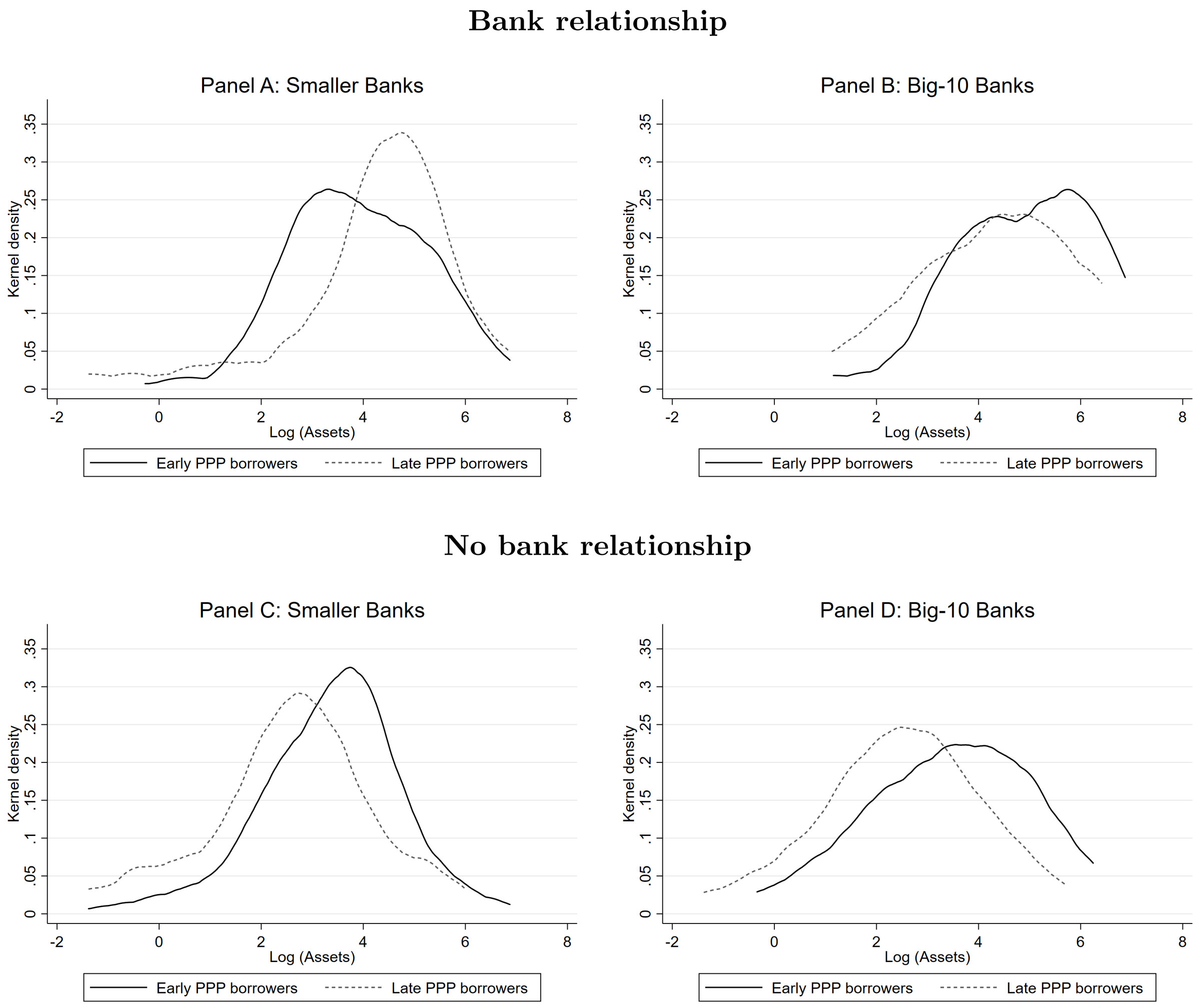

Figure 6. Early PPP access and firm assets by prior bank relationship. This figure plots kernel densities of the natural logarithm of firm's assets for early versus late public PPP borrowers, for firms with and without prior bank relationships (i.e., before the PPP). Panel A reports the results for smaller (non-big-10) banks and firms with bank relationships. Panel B reports the results for big-10 banks and firms with bank relationships. Panel C reports the results for smaller (non-big-10) banks and firms without bank relationships. Panel D reports the results for big-10 banks and firms without bank relationships. *Log (Assets)* is winsorized at the 1^{st} and the 99^{th} percentiles.

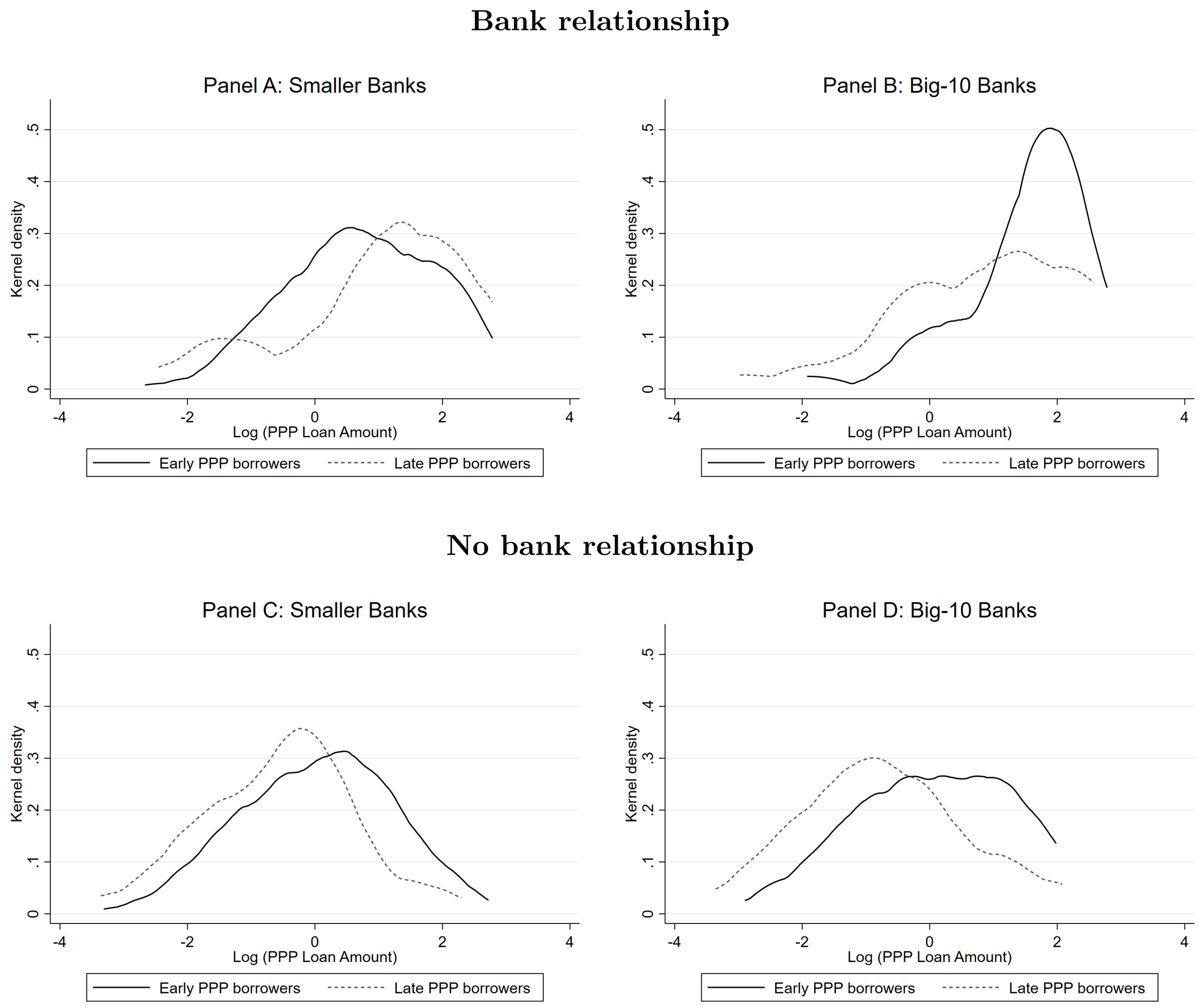

Figure 7. Early PPP access and PPP loan size by prior bank relationship. This figure plots kernel densities of the natural logarithm of PPP loan amount for early versus late public PPP borrowers, for firms with and without prior bank relationships (i.e., before the PPP). Panel A reports the results for smaller (non-big-10) banks and firms with bank relationships. Panel B reports the results for big-10 banks and firms with bank relationships. Panel C reports the results for smaller (non-big-10) banks and firms without bank relationships. Panel D reports the results for big-10 banks and firms without bank relationships. *Log (PPP Loan Amount)* is winsorized at the 1^{st} and the 99^{th} percentiles.

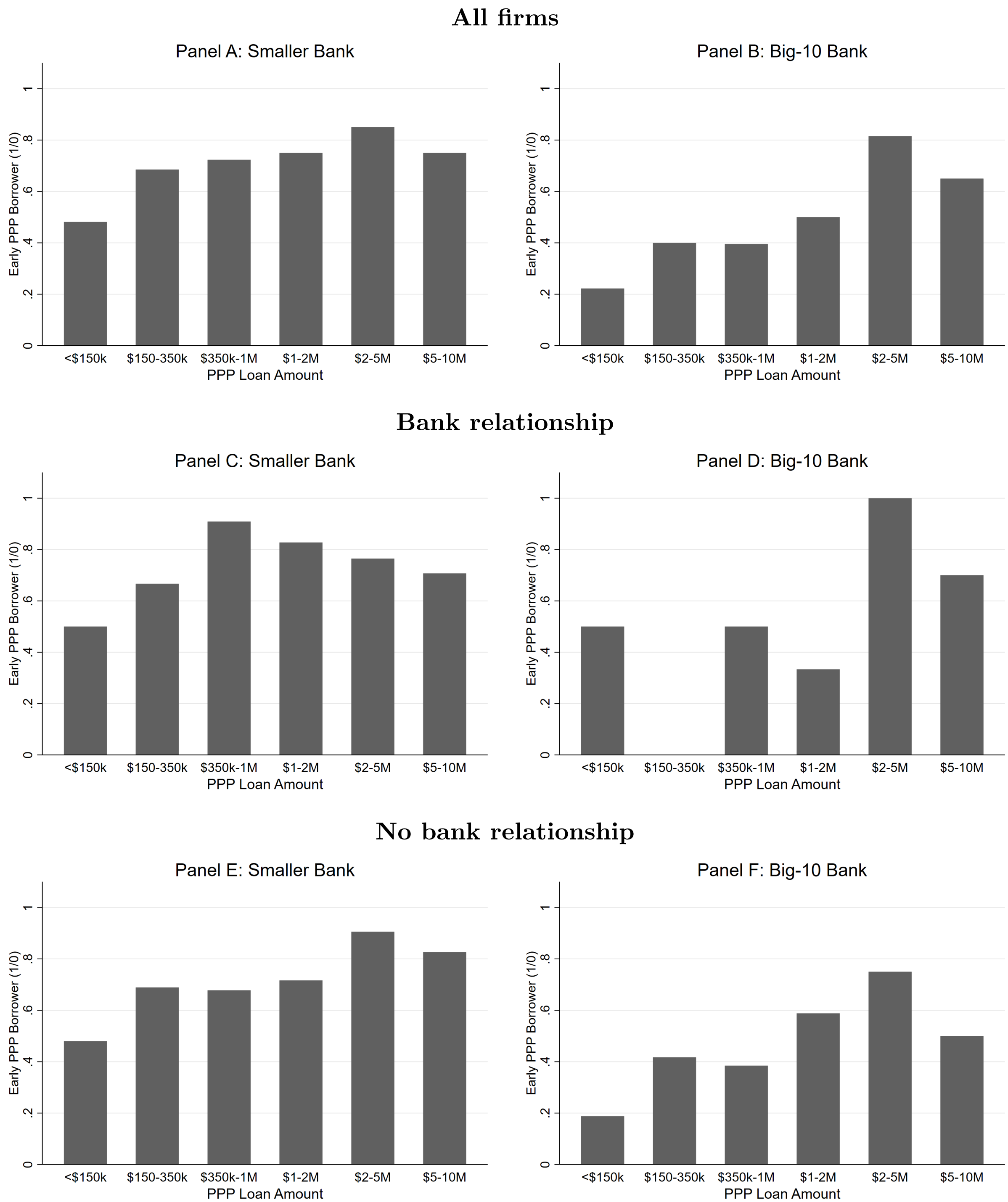

Figure 8. Probability of early PPP borrowing and PPP loan size by prior bank relationship. This figure plots the probability of borrowing early (i.e., in PPP Round 1) versus borrowing late (i.e., in PPP Round 2) for public PPP borrowers, by PPP loan size bin. Panel A reports the results for smaller (non-big-10) banks. Panel B reports the results for big-10 banks. Panel C reports the results for smaller (non-big-10) banks and firms with bank relationships. Panel D reports the results for big-10 banks and firms with bank relationships. Panel E reports the results for big-10 banks and firms without bank relationships. Panel F reports the results for smaller (non-big-10) banks and firms without bank relationships.

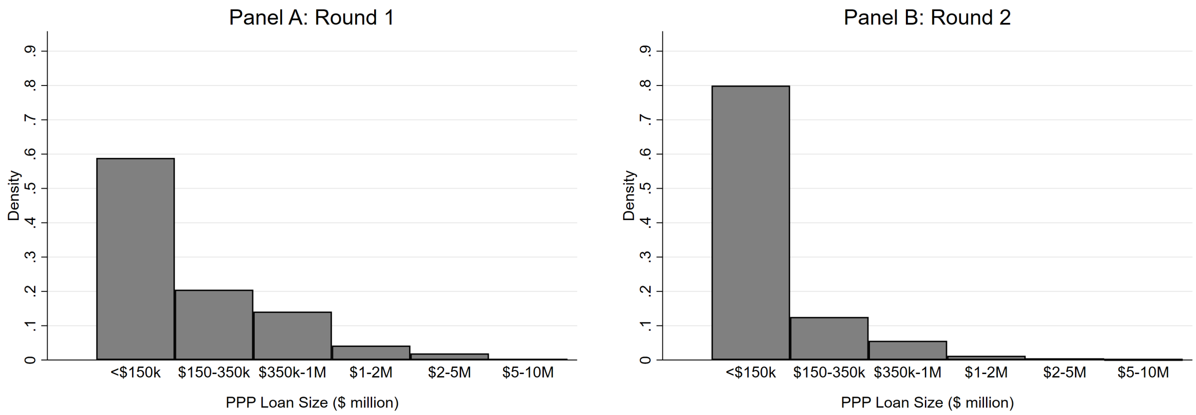

Figure 9. PPP loan size by PPP Round: SBA PPP data. This figure plots the density of PPP loan size for PPP Round 1 (before April 17, 2020) versus PPP Round 2 (after April 26, 2020). The sample is based on UCC–SBA PPP data and includes all PPP borrowers that are non-financial corporations. The results are similar if we include other types of businesses.

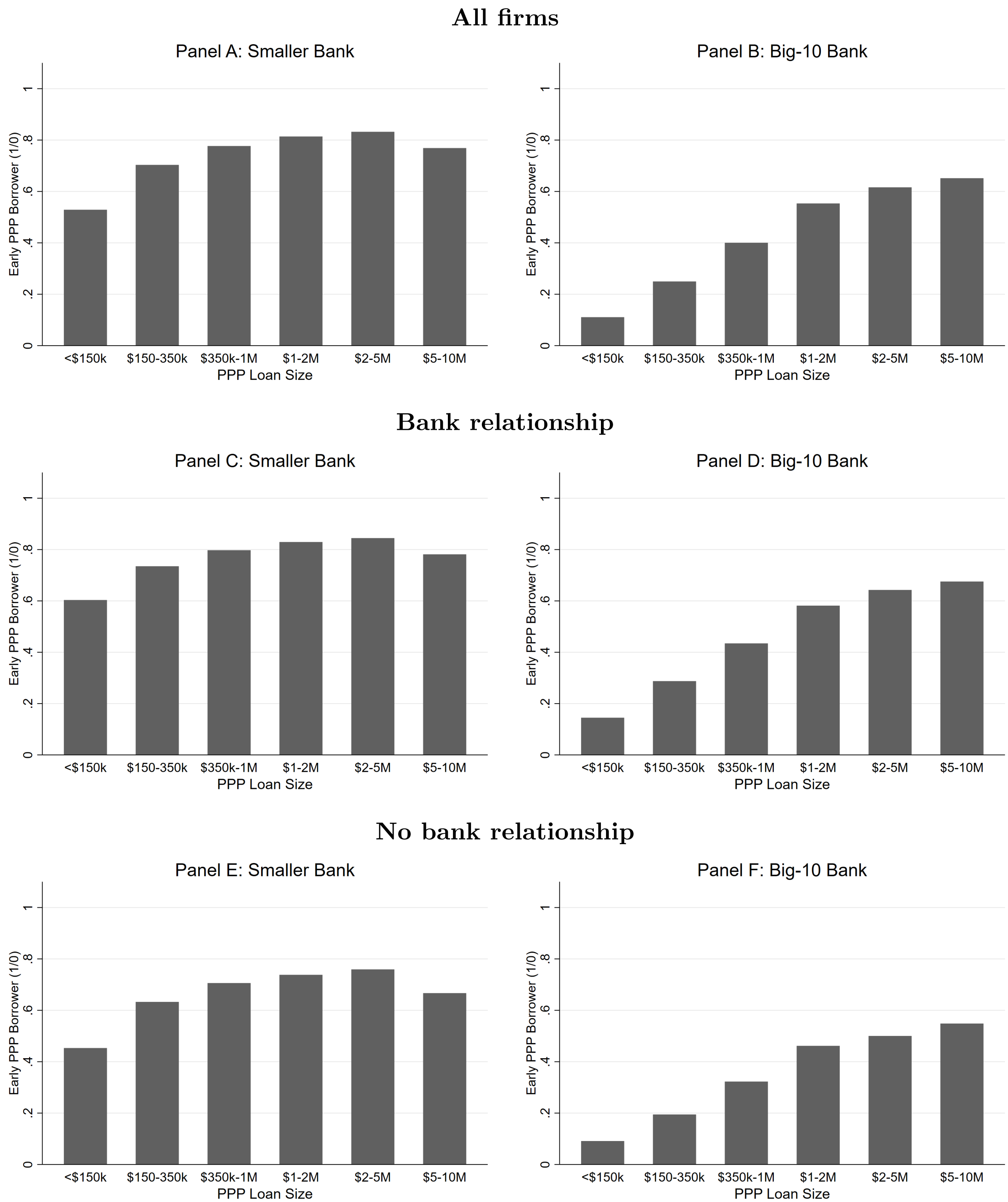

Figure 10. Probability of early PPP borrowing by prior bank relationship: SBA PPP data. This figure plots the probability of borrowing early (i.e., in PPP Round 1) versus borrowing late (i.e., in PPP Round 2) for PPP borrowers from the UCC–SBA PPP data, which we restrict to non-financial corporations, for comparability, by PPP loan size bin. Panel A reports the results for smaller (non-big-10) banks, with this category including non-bank lenders. Excluding non-bank lenders does not affect the results. Panel B reports the results for big-10 banks. Panel C reports the results for smaller (non-big-10) banks and firms with bank relationships. Panel D reports the results for big-10 banks and firms with bank relationships. Panel E reports the results for smaller (non-big-10) banks and firms without bank relationships. Panel F reports the results for big-10 banks and firms without bank relationships.

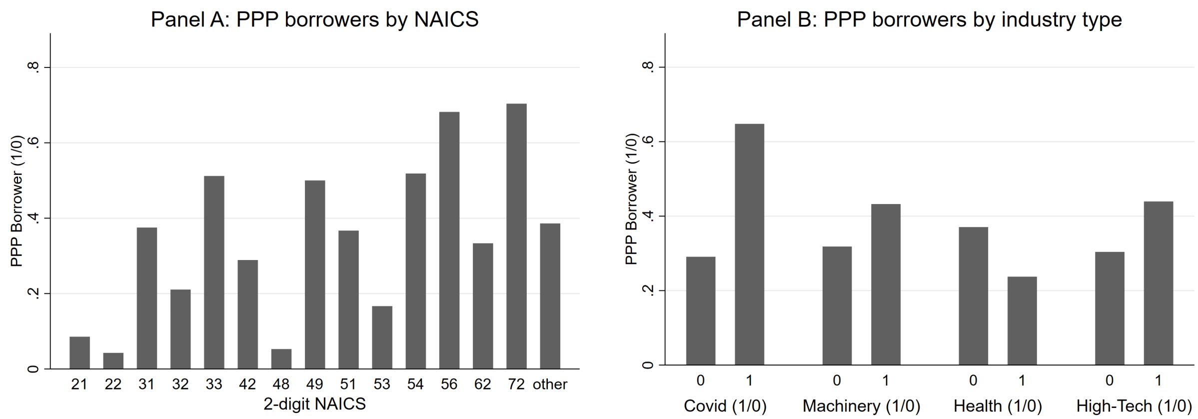

Figure 11. Public PPP borrowers by industry. This figure plots the share of PPP-eligible U.S. public companies that were granted a PPP loan, by NAICS (Panel A) and industry type (Panel B). We measure industry using 2-digit NAICS as follows: 21 = Mining, Quarrying, and Oil and Gas Extraction; 22 = Utilities; 31–33 = Manufacturing; 42 = Wholesale Trade; 48 = Transportation and Warehousing; 51 = Information; 53 = Real Estate and Rental and Leasing; 54 = Professional, Scientific, and Technical Services; 56 = Administrative and Support and Waste Management and Remediation Services; 62 = Health Care and Social Assistance; 71 = Arts, Entertainment, and Recreation; 72 = Accommodation and Food Services; and other = Other (except Public Administration).

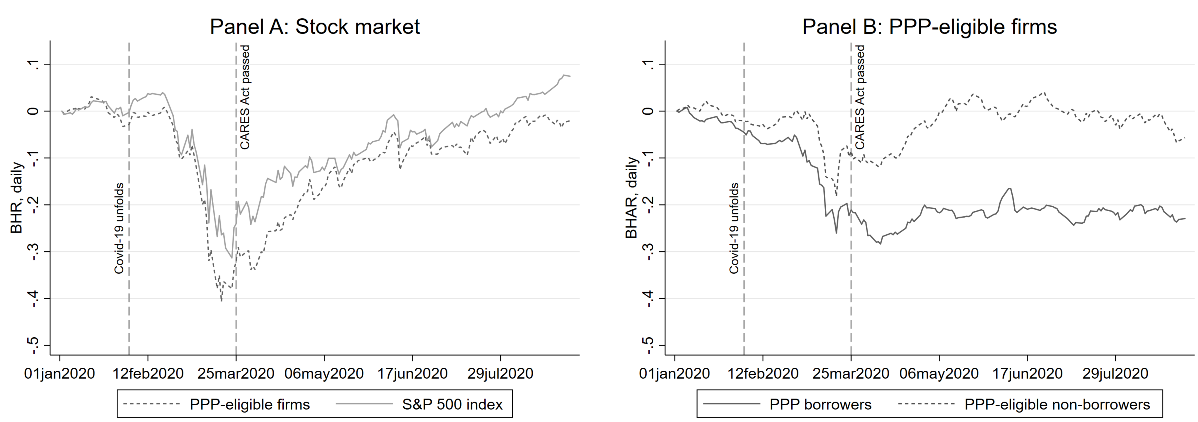

Figure 12. Evolution of PPP borrower returns: PPP applicants and control firms. This figure plots daily buy-and-hold average returns (BHRs) for PPP-eligible small public firms versus the S&P 500 index (Panel A) and buy-and-hold average abnormal returns (BHARs) for PPP borrowers versus PPP-eligible non-borrowers (Panel B), from January to August 2020. We define the abnormal return as the stock return over the S&P 500 return. We exclude penny stocks, which we define as stocks with an average share price of less than $5 in December 2019, because of illiquidity. BHAR is set to zero for the first trading day of the year, which is January 2, 2020.

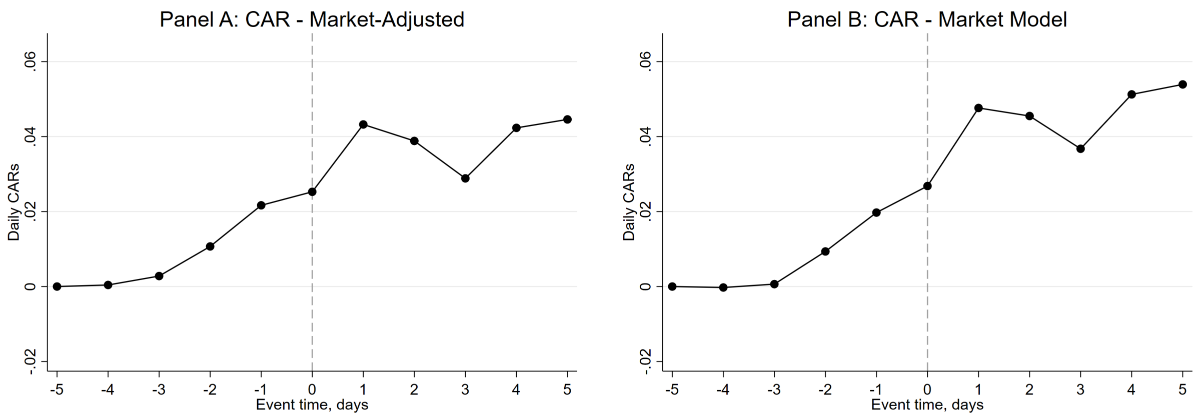

Figure 13. Cumulative abnormal returns (CARs) around PPP loan grant announcement dates. This figure plots daily CARs for PPP loan grant announcements. The abnormal return in Panel A is the stock return minus the S&P 500 return, where the abnormal return is set to zero for Day -5. The abnormal return in Panel B is calculated using the market model based on S&P 500 return, where the abnormal return is set to zero for Day -5. We exclude penny stocks, which we define as stocks with an average share price of less than $5 in December 2019.

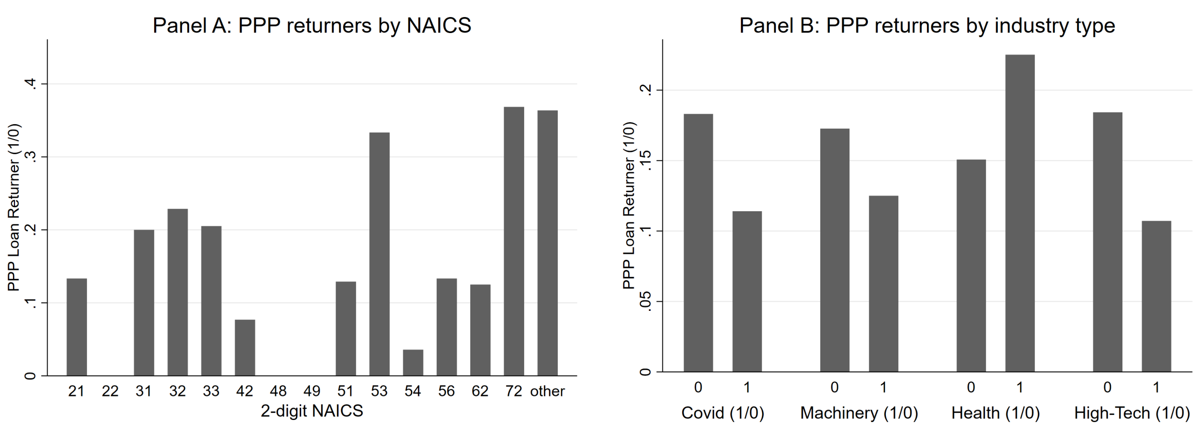

Figure 14. Firms that return PPP loans by industry. This figure plots the share of PPP borrowers that returned the PPP loans to the SBA, by NAICS (Panel A) and industry type (Panel B). See Fig. 11 for NAICS definitions.

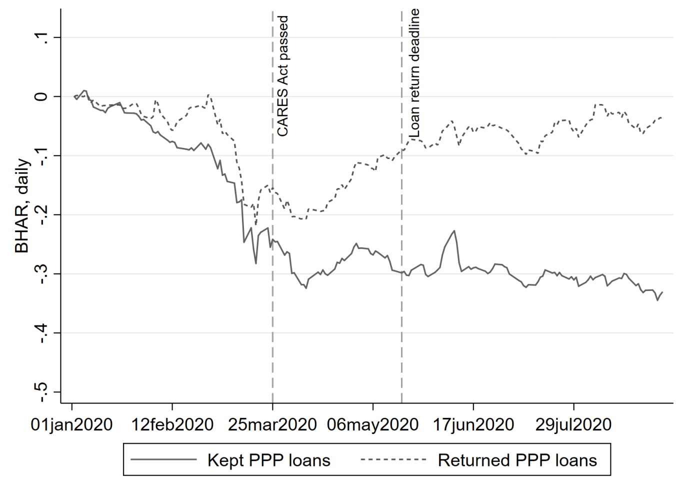

Figure 15. Evolution of PPP borrower stock returns: PPP returners and retainers. This figure plots daily buy-and-hold average abnormal returns (BHARs) for PPP returners versus retainers from January to August 2020, where the abnormal return is the stock return over the S&P 500 return. We exclude penny stocks, which we define as stocks with an average share price of less than $5 in December 2019, because of illiquidity. BHAR is set to zero for the first trading day of the year, which is January 2, 2020.

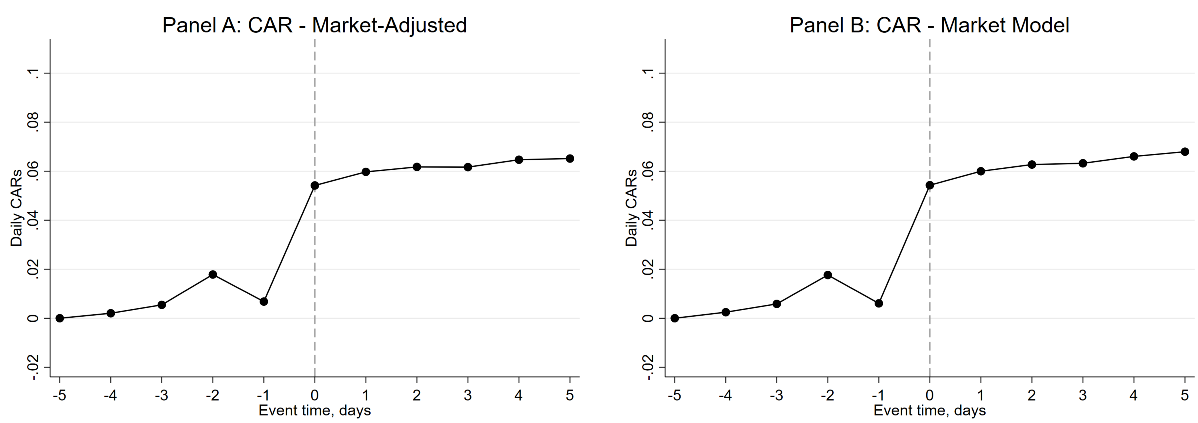

Figure 16. Cumulative abnormal returns (CARs) around PPP loan return announcement dates. This figure plots daily CARs for PPP loan return announcements. The abnormal return in Panel A is the stock return minus the S&P 500 return, where the abnormal return is set to zero for Day -5. The abnormal return in Panel B is calculated using the market model based on S&P 500 return, where the abnormal return is set to zero for Day -5. We exclude penny stocks, which we define as stocks with an average share price of less than $5 in December 2019.

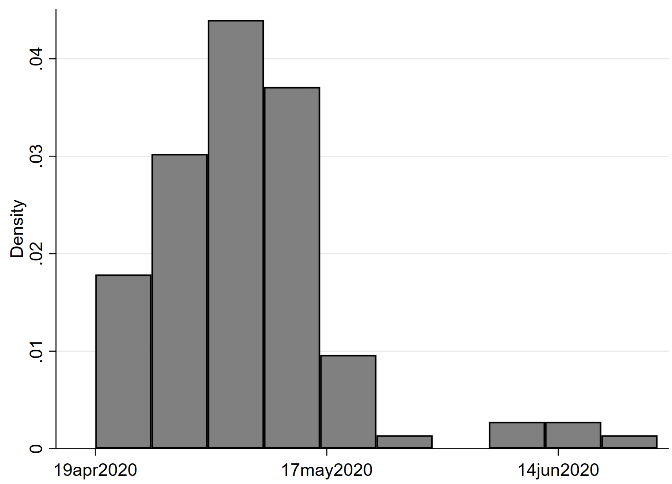

Figure 17. Density of PPP loan return announcement dates. This figure plots the density of announcement dates for returning PPP loans. We omit two announcement dates in August 2020, for the ease of exposition.

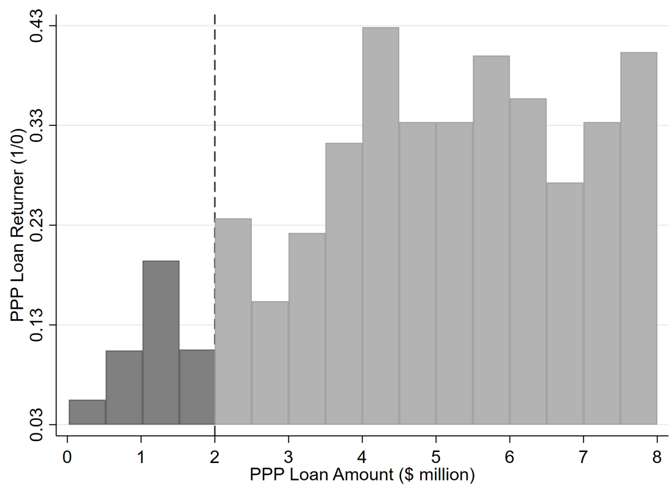

Figure 18. PPP loan return probability by loan size. This figure plots the probability of U.S. public borrowers returning PPP loans to the SBA, by PPP loan size bin. The vertical line is the loan amount of $2 million. We set PPP loan size equal to $8M for loans above $8M, for the ease of exposition.

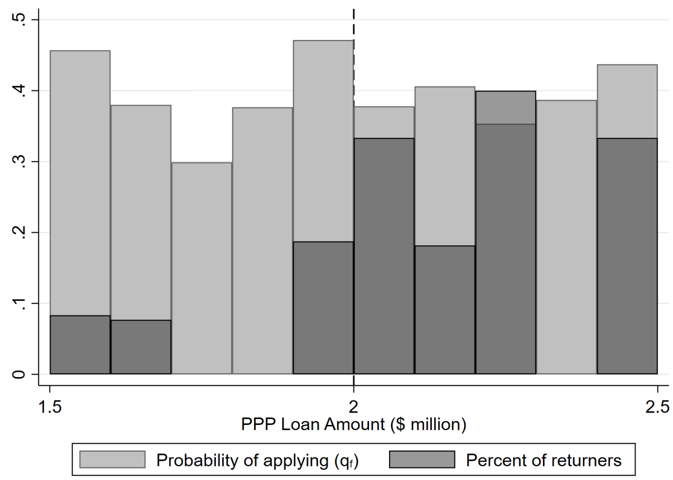

Figure 19. PPP loan return probability around the $2M loan size cutoff. This figure plots the probability of U.S. public borrowers returning PPP loans to the SBA, in the vicinity of the $2M loan size cutoff, above which the loans are subject to audit. We also plot the application probability of these firms around the cutoff. The vertical line is the loan amount of $2 million.

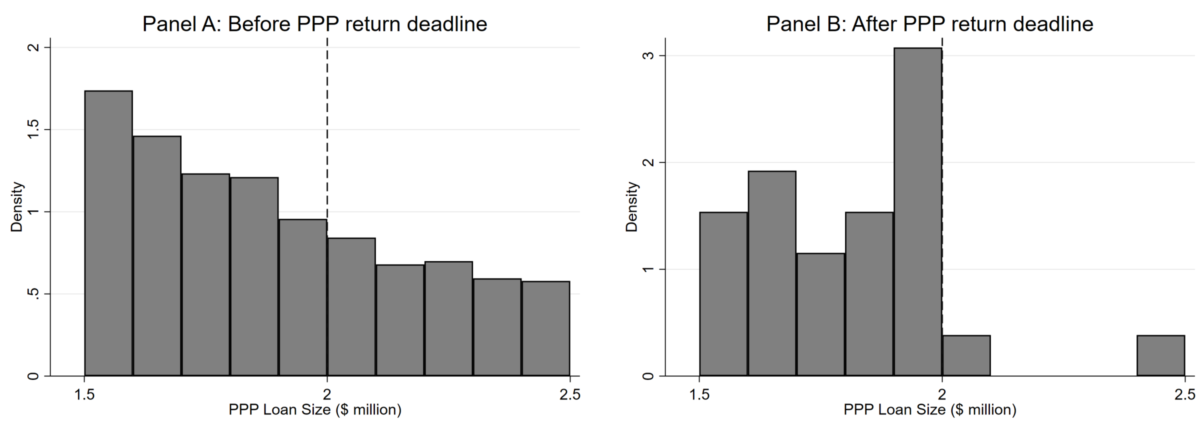

Figure 20. PPP applications around the $2M loan size cutoff: SBA PPP data. This figure plots densities of the PPP loan amount in the vicinity of the $2M loan size cutoff, above which the loans are subject to audit. The graph is based on the UCC–SBA PPP data, which we restrict to non-financial corporations, for comparability. Panel A reports the results for the period before the PPP loan return deadline on May 18, 2020. Panel B reports the results for the period after the PPP loan return deadline. The vertical line is the loan amount of $2 million.

Table 1
Full SBA PPP sample and UCC–SBA PPP sample

This table summarizes the number and the amount of PPP loans to all PPP recipients, by recipient type. Panel A reports statistics for the SBA's PPP data release in December 2020. Panel B reports statistics for the UCC–SBA PPP data.

	Number	Amount ($B)	Median	Mean
Recipient Type	(1)	(2)	(3)	(4)
Panel A: Full SBA data				
Corporation	1,498,552	207.97	41,120	138,782
LLC	1,455,353	135.25	25,000	92,935
Subchapter S	701,332	98.06	40,000	139,825
Non-Profit Organization	178,533	36.85	41,600	206,393
Sole Proprietorship	817,826	16.94	11,400	20,719
LLP	36,448	6.07	46,904	166,446
Independent Contractor	144,472	1.64	8,976	11,383
Other	324,334	20.16	15,200	62,153
Total	5,156,850	522.95	22,880	101,409
Panel B: UCC–SBA data				
Corporation	617,749	130.25	69,000	210,843
LLC	406,595	66.41	47,777	163,326
Subchapter S	247,101	60.19	80,352	243,565
Non-Profit Organization	45,705	22.90	152,500	501,119
Sole Proprietorship	84,297	4.22	20,000	50,066
LLP	14,509	3.68	76,500	253,362
Independent Contractor	2,692	0.08	13,945	30,415
Other	50,519	10.62	47,881	210,242
Total	1,469,167	298.34	59,920	203,070

Table 2
Public PPP borrower sample

Column (1) reports the number of observations at each stage of PPP borrower sample construction. Column (2) reports the respective numbers for firms that subsequently returned PPP loans to SBA.

	All PPP Borrowers	PPP Loan Returners
	(1)	(2)
1. Initial PPP borrower sample	739	123
2. Exclusions based on economic considerations:	57	6
Reason 1: Financial firm	57	6
Reason 2: Special purpose acquisition company (SPAC)	0	0
3. Final sample, including:	682	117
Matched to Compustat	586	113
Matched to Yahoo! Finance	663	117
Matched to SBA's PPP loan disclosures (Jul, Aug, or Dec)	538	17
Matched to Lender RSSD IDs (e.g., FDIC, FFIEC, NCUA)	623	92
Matched to DealScan & UCC	405	82
4. PPP announcements, including:	682	117
PPP announcements from 8-K filings	439	68
PPP announcements from 10-Qs, 10-Ks, and other sources	243	49
5. PPP borrowing disclosed after PPPFA	258	8

Table 3
Public and private PPP borrowers by PPP round

Columns (1) to (3) report the mean, median, and standard deviation of several financial characteristics of firms that obtained PPP loans in PPP Round 1. Columns (4) to (6) report the same statistics for firms that obtained PPP loans in PPP Round 2. Column (7) reports the number of observations and Column (8) reports p-values from a Wilcoxon rank sum test comparing early borrowers with late borrowers. In the case of discrete variables, the statistics are proportions and the p-values are for tests of the difference in proportions. Variables are defined in Internet Appendix Section IA.D. Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles.

	Early PPP borrowers			Late PPP borrowers			Difference tests	
	Mean	Median	SD	Mean	Median	SD	N	p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Public PPP borrower sample								
Firm size								
PPP Loan Amount ($ million)	2.671	1.482	3.084	1.982	0.723	3.098	679	0.000
Book Value of Assets ($ million)	120.3	39.2	520.2	99.8	23.3	367.7	569	0.000
Market Cap ($ million)	115.4	41.6	282.6	101.4	24.6	297.1	561	0.000
Sales ($ million)	77.8	25.8	160.9	86.8	11.1	229.8	569	0.000
# Employees ('000)	0.254	0.109	0.380	0.217	0.061	0.359	561	0.000
Other financial characteristics								
Firm Age (years)	15.694	12.000	12.958	15.315	10.500	13.104	569	0.199
Book Equity <0 (1/0)	17.7%	—	—	32.1%	—	—	568	0.000
Tobin's Q	1.773	1.201	2.181	1.516	0.972	2.188	569	0.001
Sales Growth	0.617	0.032	3.484	0.468	0.002	2.536	511	0.571
Dividend Payer (1/0)	15.3%	—	—	13.6%	—	—	569	0.172
Current Ratio	2.651	1.876	2.872	2.551	1.407	4.150	568	0.002
Cash/Non-Cash Assets	1.086	0.237	3.353	1.086	0.215	2.730	569	0.587
Free Cash Flow/Assets	0.144	0.032	0.872	0.327	0.047	2.106	477	0.235
Financial constraints								
Has Credit Rating (1/0)	2.7%	—	—	2.6%	—	—	682	0.531
WW Index $\geq$ p75 (1/0)	72.4%	—	—	71.0%	—	—	406	0.857
SA Index $\geq$ p75 (1/0)	76.1%	—	—	79.5%	—	—	527	0.641
Leverage and distress								
Zero Debt (1/0)	8.6%	—	—	9.2%	—	—	569	0.410
Market Leverage	0.234	0.165	0.224	0.303	0.212	0.295	512	0.297
Interest Coverage <1.5 (1/0)	77.3%	—	—	80.1%	—	—	436	0.725
Altman Z-score <1.81 (1/0)	67.8%	—	—	71.2%	—	—	479	0.616
Distance-to-Default	2.743	2.368	2.075	2.534	1.960	2.030	409	0.087
Penny Stock (1/0)	72.4%	—	—	81.1%	—	—	561	0.222
Stock returns								
Covid Period Return	-0.322	-0.388	0.383	-0.309	-0.387	0.379	638	0.800
Stimulus Day Return	0.059	0.049	0.109	0.047	0.030	0.127	644	0.022
Panel B: Full SBA PPP sample and UCC–SBA PPP sample								
Full SBA data								
PPP Loan Size ($ million)	0.209	0.080	0.349	0.084	0.032	0.183	1,297,214	0.000
# Jobs ('000)	0.040	0.018	0.062	0.018	0.008	0.036	1,211,239	0.000
UCC–SBA data								
PPP Loan Size ($ million)	0.278	0.110	0.452	0.128	0.050	0.269	560,829	0.000
# Jobs ('000)	0.050	0.022	0.077	0.024	0.010	0.048	526,684	0.000

Table 4
Early PPP borrower propensity

This table reports the results from a linear regression in which the dependent variable is an indicator for public company receiving a PPP loan before April 17, 2020 when the PPP funds ran out and independent variables are company characteristics. Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles. Standard errors are clustered at the industry level, defined as 2-digit NAICS, where we combine industries with few PPP-eligible companies into one bucket. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. t-statistics are presented in parentheses.

	Dependent variable = Early PPP Borrower (1/0)		
	(1)	(2)	(3)
Log (Assets)	0.0338**	0.0325**	0.0370**
	(2.48)	(2.20)	(2.74)
Log (Age)	0.00373	0.00412	0.00353
	(0.12)	(0.13)	(0.11)
Book Equity <0 (1/0)	-0.141***	-0.132**	-0.127**
	(-3.05)	(-2.73)	(-2.54)
Tobin's Q	-0.00162	-0.000765	0.00448
	(-0.08)	(-0.04)	(0.24)
Current Ratio	-0.00537	-0.00510	-0.00611
	(-1.00)	(-0.93)	(-1.14)
Cash/Non-Cash Assets	0.00417	0.00385	0.00429
	(1.51)	(1.38)	(1.57)
Penny Stock (1/0)	-0.0414	-0.0432	-0.0115
	(-0.71)	(-0.73)	(-0.21)
Covid Industry (1/0)		0.00389	0.0112
		(0.06)	(0.14)
Machinery Industry (1/0)		0.140*	0.152*
		(1.80)	(2.07)
Health Industry (1/0)		-0.00694	-0.0196
		(-0.19)	(-0.49)
High-Tech Industry (1/0)		-0.0494	-0.0513
		(-1.11)	(-1.22)
Covid Period Return			-0.161
			(-1.61)
Covid Period Return × Penny Stock (1/0)			0.191*
			(2.08)
Stimulus Day Return			-0.590
			(-1.49)
Stimulus Day Return × Penny Stock (1/0)			0.570
			(1.59)
# obs.	543	543	535
Adjusted R^2	0.0321	0.0291	0.0256

Table 5
Early versus late PPP access, small versus big banks, and bank relationships

This table compares the size of early versus late PPP borrowers that obtained a PPP loan through one of big-10 banks (*Big-10 Bank*) versus other banks (*Smaller Bank*). Panel A reports the results for all firms. Panel B reports the results for firms with prior bank relationships. Panel C reports the results for firms without prior bank relationships. We classify the following banks as big-10 banks: JPMorgan Chase Bank, Wells Fargo Bank, Bank of America, Citibank, U.S. Bank, Truist Bank, PNC Bank, Bank of New York, State Street Corporation, and TD Bank. Columns (1) to (2) report means and medians of the size variable for firms that obtained PPP loans in PPP Round 1 (i.e., early PPP borrowers). Columns (3) to (4) report the respective means and medians for PPP Round 2 (i.e., late PPP borrowers). Column (5) reports the number of observations and Column (6) reports p-values from a Wilcoxon rank sum test comparing early borrowers with late borrowers. Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles.

	Early PPP borrowers		Late PPP borrowers		Difference tests	
	mean	median	mean	median	N	p-value
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All firms						
Smaller banks						
Book Value of Assets	82.402	36.385	86.682	26.979	372	0.093
PPP Loan Amount	2.468	1.404	2.216	0.862	440	0.004
Big-10 banks						
Book Value of Assets	144.158	55.110	61.366	18.625	153	0.000
PPP Loan Amount	3.428	2.220	1.848	0.588	179	0.000
Panel B: Bank relationship						
Smaller banks						
Book Value of Assets	118.763	43.079	178.308	94.652	125	0.119
PPP Loan Amount	3.577	2.124	5.267	3.558	137	0.138
Big-10 banks						
Book Value of Assets	247.562	161.465	151.072	68.755	48	0.158
PPP Loan Amount	6.069	5.533	4.428	1.639	53	0.150
Panel C: No bank relationship						
Smaller banks						
Book Value of Assets	64.317	34.813	37.709	14.878	247	0.000
PPP Loan Amount	1.932	1.054	1.091	0.681	303	0.000
Big-10 banks						
Book Value of Assets	80.047	37.745	33.638	11.947	105	0.003
PPP Loan Amount	1.880	1.087	1.127	0.464	126	0.001

Table 6
Early PPP access, lender effects, and bank relationships

This table reports the results from a linear regression in which the dependent variable is an indicator for an early public PPP borrower. An early borrower is a company receiving a PPP loan before April 17, 2020. The size variable is *Book Value of Assets* in Panel A and *PPP Loan Amount* in Panel B. *Smaller Bank (1/0)* is a dummy for PPP lender being a non-big-10 bank. We classify the following banks as big-10 banks: JPMorgan Chase Bank, Wells Fargo Bank, Bank of America, Citibank, U.S. Bank, Truist Bank, PNC Bank, Bank of New York, State Street Corporation, and TD Bank. Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles. Standard errors are clustered at the industry level, defined as 2-digit NAICS, where we combine industries with few PPP-eligible companies into one bucket. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. *t*-statistics are presented in parentheses. Constants are omitted for brevity. Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles.

	Dependent variable = Early PPP Borrower (1/0)					
	All firms		Bank relationship		No bank relationship	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Firm size						
Log (Assets) × Smaller Bank (1/0)	-0.0547**	-0.0583**	-0.0960*	-0.120**	-0.0224*	-0.0209
	(-2.22)	(-2.63)	(-2.07)	(-2.38)	(-1.80)	(-1.65)
Log (Assets)	0.0875***	0.0692***	0.0752**	0.0540	0.0880***	0.0795***
	(5.22)	(3.04)	(2.51)	(1.18)	(7.52)	(4.15)
Smaller Bank (1/0)	0.421***	0.429***	0.538**	0.651**	0.338***	0.319***
	(4.10)	(4.70)	(2.68)	(2.61)	(4.25)	(4.57)
Firm Characteristics	No	Yes	No	Yes	No	Yes
Penny Stock Dummy	No	Yes	No	Yes	No	Yes
Industry Dummies	No	Yes	No	Yes	No	Yes
Returns Controls	No	Yes	No	Yes	No	Yes
# obs.	525	493	173	167	352	326
Adjusted R^2	0.0884	0.0705	0.0131	0.0415	0.132	0.0941
Panel B: PPP loan size						
Log (PPP Loan Size) × Smaller Bank (1/0)	-0.00813	-0.0297*	-0.0438	-0.103**	0.0231	0.0126
	(-0.38)	(-1.77)	(-0.80)	(-2.98)	(1.39)	(0.55)
Log (PPP Loan Size)	0.0664**	0.0602**	0.0360	0.0518	0.0750***	0.0763***
	(2.54)	(2.43)	(0.68)	(0.92)	(3.22)	(3.02)
Smaller Bank (1/0)	0.260**	0.333***	0.303	0.581**	0.199**	0.221**
	(2.58)	(4.22)	(1.16)	(2.87)	(2.66)	(2.90)
Firm Characteristics	No	Yes	No	Yes	No	Yes
Penny Stock Dummy	No	Yes	No	Yes	No	Yes
Industry Dummies	No	Yes	No	Yes	No	Yes
Returns Controls	No	Yes	No	Yes	No	Yes
# obs.	525	493	173	167	352	326
Adjusted R^2	0.0760	0.0672	0.00146	0.0408	0.127	0.0956

Table 7
Early PPP access and bank relationships:
SBA PPP data

This table reports the results from a linear regression in which the dependent variable is an indicator for an early PPP borrower. The sample is the UCC–SBA PPP dataset. An early borrower is a company receiving a PPP loan before April 17, 2020. Column 1 estimated the regression based on all firms in the dataset. Columns 2 (3) use the subsample of firms with (without) a bank relationship before the PPP. A firm has a bank relationship if it is recorded as having a security interest filing under UCC between 2015 and 2019. *Log (PPP Loan Size)* is the natural logarithm of the PPP loan size from the SBA PPP data, which we restrict to non-financial corporations, for comparability. *Smaller Bank (1/0)* is a dummy for PPP lender being a non-big-10 bank. We classify the following banks as big-10 banks: JPMorgan Chase Bank, Wells Fargo Bank, Bank of America, Citibank, U.S. Bank, Truist Bank, PNC Bank, Bank of New York, State Street Corporation, and TD Bank. Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles. Standard errors are clustered at the industry level, defined as 2-digit NAICS, where we combine industries with few PPP-eligible companies into one bucket. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. t-statistics are presented in parentheses. Constants are omitted for brevity. Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles.

	Dependent variable = Early PPP Borrower (1/0)		
	All firms	Bank relationship	No bank relationship
	(1)	(2)	(3)
Log (PPP Loan Size) × Smaller Bank (1/0)	0.0262***	-0.00510	0.0488***
	(6.73)	(-1.58)	(12.85)
Log (PPP Loan Size)	0.0784***	0.0976***	0.0543***
	(22.10)	(33.60)	(12.99)
Smaller Bank (1/0)	0.357***	0.303***	0.403***
	(34.71)	(39.89)	(37.63)
NAICS-6 FEs	Yes	Yes	Yes
ZIP-5 FEs	Yes	Yes	Yes
# obs.	549,390	298,842	244,967
Adjusted R^2	0.284	0.254	0.266

Table 8
Early PPP access and Applying Through Relationship Bank
SBA PPP data

This table reports the results from linear regression in which the dependent variable is an indicator for an early PPP borrower. The sample includes all firms in the UCC–SBA PPP data that have a bank relationships before the PPP. A firm has a bank relationship if it is recorded as having a security interest filing under UCC between 2015 and 2019. An early borrower is a company receiving a PPP loan before April 17, 2020. *Relationship Bank PPP* is a dummy variable for whether the firm applies through its relationship bank. *Small Bank Relationship* is a dummy variable for whether the firm had a relationship with a small bank. We classify the following banks as big-10 banks: JPMorgan Chase Bank, Wells Fargo Bank, Bank of America, Citibank, U.S. Bank, Truist Bank, PNC Bank, Bank of New York, State Street Corporation, and TD Bank. Standard errors are clustered at the industry level, defined as 2-digit NAICS, where we combine industries with few PPP-eligible companies into one bucket. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. t-statistics are presented in parentheses. Constants are omitted for brevity. Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles.

	Dependent variable = Early PPP Borrower (1/0)		
	(1)	(2)	(3)
Relationship Bank PPP (1/0)	0.0950***		-0.102***
	(17.38)		(-13.97)
Small Bank Relationship (1/0)		0.213***	0.0971***
		(32.29)	(16.14)
Relationship Bank PPP (1/0) × Small Bank Relationship (1/0)			0.242***
			(47.74)
NAICS-6 FEs	Yes	Yes	Yes
ZIP-5 FEs	Yes	Yes	Yes
# obs.	298,842	298,842	298,842
Adjusted R^2	0.150	0.169	0.186

Table 9
Publicly listed PPP applicants and control firms

Columns (1) to (3) report the mean, median, and standard deviation of several financial characteristics of firms that applied for PPP loans. Columns (4) to (6) report the same statistics for the control group of firms with fewer than 500 employees reported in COMPUSTAT that did not apply for the PPP. Column (7) reports the number of observations and Column (8) reports p-values from a Wilcoxon rank sum test comparing applicants with non-applicants. In the case of discrete variables, the statistics are proportions and the p-values are for tests of the difference in proportions. Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles.

	PPP borrowers (N=682)			Non-applicants (N=1,452)			Difference tests	
	Mean	Median	SD	Mean	Median	SD	N	p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Firm size								
PPP Loan Amount ($ million)	2.434	1.139	3.104	—	—	—	679	—
Book Value of Assets ($ million)	113.7	34.8	476.0	526.3	84.7	1,503.0	2,021	0.000
Market Cap ($ million)	110.9	35.9	287.1	487.8	118.7	951.6	1,947	0.000
Sales ($ million)	80.7	22.9	185.8	120.8	13.0	299.2	2,021	0.000
# Employees ('000)	0.242	0.090	0.373	0.116	0.059	0.132	2,013	0.000
Other financial characteristics								
Firm Age (years)	15.571	12.000	12.995	9.873	7.000	9.740	2,021	0.000
Book Equity <0 (1/0)	22.4%	—	—	15.9%	—	—	2,019	0.000
Tobin's Q	1.690	1.140	2.185	2.592	1.333	3.875	2,021	0.000
Sales Growth	0.570	0.024	3.216	0.672	0.037	3.176	1,545	0.845
Dividend Payer (1/0)	14.8%	—	—	14.3%	—	—	2,021	0.546
Current Ratio	2.619	1.692	3.337	5.017	2.451	7.207	2,004	0.000
Cash/Non-Cash Assets	1.086	0.233	3.162	3.501	0.400	7.733	2,007	0.000
Free Cash Flow/Assets	0.203	0.033	1.392	0.392	0.011	2.750	1,682	0.000
Financial constraints								
Has Credit Rating (1/0)	2.6%	—	—	5.7%	—	—	2,134	0.000
WW Index $\geq$ p75 (1/0)	71.9%	—	—	46.5%	—	—	1,262	0.000
SA Index $\geq$ p75 (1/0)	77.2%	—	—	72.7%	—	—	1,872	0.248
Leverage and distress								
Zero Debt (1/0)	8.8%	—	—	15.5%	—	—	2,018	0.000
Market Leverage	0.256	0.178	0.251	0.228	0.100	0.270	1,682	0.000
Interest Coverage <1.5 (1/0)	78.2%	—	—	76.8%	—	—	1,457	0.749
Altman Z-score <1.81 (1/0)	68.9%	—	—	61.0%	—	—	1,623	0.030
Distance-to-Default	2.685	2.254	2.062	3.713	3.137	2.486	961	0.000
Penny Stock (1/0)	75.2%	—	—	59.5%	—	—	1,948	0.000
Stock returns								
Covid Period Return	-0.318	-0.387	0.381	-0.327	-0.361	0.310	2,028	0.136
Stimulus Day Return	0.055	0.042	0.116	0.058	0.049	0.103	2,042	0.078

Table 10
PPP borrowing propensity

This table reports the results from a linear probability (OLS) model where the dependent variable is an indicator for public company receiving a PPP loan and independent variables are company characteristics. Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles. Standard errors are clustered at the industry level, defined as 2-digit NAICS, where we combine industries with few PPP-eligible companies into one bucket. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. t-statistics are presented in parentheses.

	Dependent variable = PPP Borrower (1/0)		
	(1)	(2)	(3)
Log (Assets)	-0.0350***	-0.0268***	-0.0255**
	(-3.81)	(-4.10)	(-2.86)
Log (Age)	0.0635***	0.0639***	0.0646**
	(3.45)	(3.09)	(2.88)
Book Equity <0 (1/0)	-0.0602	-0.0606	-0.0635
	(-1.53)	(-1.45)	(-1.48)
Tobin's Q	-0.0134***	-0.0126***	-0.0128***
	(-4.70)	(-4.19)	(-3.74)
Current Ratio	-0.00725***	-0.00642***	-0.00622***
	(-3.78)	(-3.37)	(-3.28)
Cash/Non-Cash Assets	-0.00558***	-0.00578***	-0.00556**
	(-3.67)	(-3.05)	(-2.77)
Penny Stock (1/0)	0.00162	0.0114	0.0728
	(0.03)	(0.30)	(1.66)
Covid Industry (1/0)		0.331**	0.334**
		(2.82)	(2.88)
Machinery Industry (1/0)		0.127	0.134
		(1.07)	(1.03)
Health Industry (1/0)		0.0510	0.0502
		(0.46)	(0.44)
High-Tech Industry (1/0)		0.134	0.144
		(1.13)	(1.23)
Covid Period Return			-0.129
			(-1.56)
Covid Period Return × Penny Stock (1/0)			0.157*
			(2.06)
Stimulus Day Return			0.158
			(0.39)
Stimulus Day Return × Penny Stock (1/0)			0.124
			(0.33)
# obs.	1,797	1,797	1,762
Adjusted R^2	0.0798	0.111	0.114

Table 11
PPP loan grant announcement effects

This table reports the results from a event study analysis where the dependent variable is the company's stock return measured as stock return minus S&P 500 return (Panel A) or abnormal stock return calculated using the market model based on S&P 500 return (Panel B). The key independent variable *Day* is an indicator for the treading day relative to the PPP loan grant announcement date, *Day 0* (e.g., 8-K filing, press release). The time period is from Day -60 to Day +1. The estimation window for the market model is Day -270 to Day -61. The day count excludes non-trading days (e.g., weekends, holidays). Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles. Standard errors are clustered at the trading day level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. *t*-statistics are presented in parentheses.

	Panel A: Market-adjusted			Panel B: Market model		
	Day -1	Day 0	Day +1	Day -1	Day 0	Day +1
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All observations						
Across firms						
Abnormal return	0.0112**	0.00307	0.00194	0.0114***	0.00533	0.00530
t-statistic	(2.43)	(0.64)	(0.39)	(2.88)	(1.15)	(1.28)
Within firms						
Abnormal return	0.0112**	0.00309	0.00195	0.0114***	0.00534	0.00531
t-statistic	(2.42)	(0.63)	(0.38)	(2.88)	(1.12)	(1.28)
Panel B: Only 8-K filings						
Across firms						
Abnormal return	0.0159***	0.00431	0.00676	0.0157***	0.00652	0.00850
t-statistic	(3.68)	(0.74)	(1.26)	(3.97)	(1.14)	(1.66)
Within firms						
Abnormal return	0.0159***	0.00435	0.00680	0.0158***	0.00656	0.00853*
t-statistic	(3.70)	(0.74)	(1.28)	(3.98)	(1.13)	(1.70)
Panel C: Only 8-K filings & non-penny stocks						
Across firms						
Abnormal return	0.0175***	0.00741	0.0106	0.0165***	0.0108	0.0122
t-statistic	(3.22)	(0.97)	(1.43)	(2.88)	(1.25)	(1.61)
Within firms						
Abnormal return	0.0175***	0.00742	0.0106	0.0165***	0.0108	0.0122
t-statistic	(3.23)	(0.98)	(1.39)	(2.95)	(1.24)	(1.57)

Table 12
Public PPP returners versus retainers

Columns (1) to (3) report the mean, median, and standard deviation of several financial characteristics of firms that returned PPP loans to SBA. Columns (4) to (6) report the same statistics for firms that retained PPP loans. Column (7) reports the number of observations and Column (8) reports p-values from a Wilcoxon rank sum test comparing returners with retainers. In the case of discrete variables, the statistics are proportions and the p-values are for tests of the difference in proportions. Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles.

	Returned PPP loan (N=117)			Retained PPP loan (N=565)			Difference tests	
	Mean	Median	SD	Mean	Median	SD	N	p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Firm size								
PPP Loan Amount ($ million)	4.430	3.330	4.105	2.023	0.956	2.681	679	0.000
Book Value of Assets ($ million)	288.4	86.0	1,032.0	71.4	27.7	126.7	569	0.000
Market Cap ($ million)	276.1	118.0	565.1	71.0	28.2	133.0	561	0.000
Sales ($ million)	159.1	49.6	321.5	61.7	19.2	127.2	569	0.000
# Employees ('000)	0.390	0.215	0.467	0.206	0.077	0.337	561	0.000
Other financial characteristics								
Firm Age (years)	17.441	13.000	14.627	15.118	11.000	12.544	569	0.327
Book Equity <0 (1/0)	11.7%	—	—	24.9%	—	—	568	0.000
Tobin's Q	2.085	1.432	2.693	1.594	1.063	2.035	569	0.000
Sales Growth	0.464	0.070	2.695	0.597	0.011	3.337	511	0.018
Dividend Payer (1/0)	24.3%	—	—	12.4%	—	—	569	0.000
Current Ratio	3.845	2.548	4.814	2.321	1.504	2.793	568	0.000
Cash/Non-Cash Assets	1.131	0.405	2.050	1.075	0.211	3.379	569	0.003
Free Cash Flow/Assets	0.137	0.017	1.115	0.218	0.043	1.449	477	0.152
Financial constraints								
Has Credit Rating (1/0)	6.0%	—	—	1.9%	—	—	682	0.000
WW Index $\geq$ p75 (1/0)	51.3%	—	—	76.7%	—	—	406	0.001
SA Index $\geq$ p75 (1/0)	62.7%	—	—	80.7%	—	—	527	0.015
Leverage and distress								
Zero Debt (1/0)	12.6%	—	—	7.9%	—	—	569	0.000
Market Leverage	0.187	0.118	0.199	0.272	0.199	0.259	512	0.003
Interest Coverage <1.5 (1/0)	61.5%	—	—	81.8%	—	—	436	0.014
Altman Z-score <1.81 (1/0)	48.3%	—	—	73.6%	—	—	479	0.000
Distance-to-Default	3.807	3.043	2.349	2.336	1.953	1.834	409	0.000
Penny Stock (1/0)	53.2%	—	—	80.5%	—	—	561	0.000
Stock returns								
Covid Period Return	-0.332	-0.384	0.362	-0.315	-0.388	0.386	638	0.823
Stimulus Day Return	0.070	0.065	0.091	0.052	0.036	0.120	644	0.020
PPP Grant Abnormal Return	0.031	0.017	0.108	0.021	0.001	0.127	646	0.151

Table 13
PPP loan return propensity

This table reports the results from a linear probability (OLS) model where the dependent variable is an indicator for public company returning a PPP loan to the SBA and independent variables are company characteristics. Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles. Standard errors are clustered at the industry level, defined as 2-digit NAICS, where we combine industries with few PPP-eligible companies into one bucket. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. t-statistics are presented in parentheses.

	Dependent variable = PPP Loan Returner (1/0)		
	(1)	(2)	(3)
Log (Assets)	0.0560***	0.0540***	0.0563***
	(4.44)	(4.36)	(3.99)
Log (Age)	-0.00962	-0.00134	-0.00225
	(-0.78)	(-0.10)	(-0.18)
Book Equity <0 (1/0)	0.0311	0.0226	0.0206
	(0.56)	(0.45)	(0.45)
Tobin's Q	0.0121***	0.00826**	0.00696*
	(3.68)	(2.47)	(1.83)
Current Ratio	0.0168***	0.0158***	0.0163***
	(3.50)	(3.11)	(3.25)
Cash/Non-Cash Assets	0.000876	-0.000548	0.000252
	(0.21)	(-0.12)	(0.05)
Penny Stock (1/0)	-0.112**	-0.122**	-0.214*
	(-2.22)	(-2.74)	(-2.09)
Covid Industry (1/0)		-0.0309	-0.0318
		(-1.35)	(-1.24)
Machinery Industry (1/0)		-0.0695**	-0.0813**
		(-2.56)	(-2.38)
Health Industry (1/0)		0.0814**	0.0836**
		(2.30)	(2.65)
High-Tech Industry (1/0)		-0.0367	-0.0362
		(-1.48)	(-1.25)
Covid Period Return			0.297**
			(2.65)
Covid Period Return × Penny Stock (1/0)			-0.239
			(-1.70)
Stimulus Day Return			0.140
			(0.44)
Stimulus Day Return × Penny Stock (1/0)			-0.157
			(-0.60)
PPP Grant Abnormal Return			0.158
			(0.36)
PPP Grant Abnormal Return × Penny Stock (1/0)			0.0424
			(0.08)
# obs.	543	543	535
Adjusted R^2	0.110	0.116	0.118

Table 14
PPP loan return announcement effects

This table reports the results from a event study analysis where the dependent variable is the company's stock return measured as stock return minus S&P 500 return (Panel A) or abnormal stock return calculated using the market model based on S&P 500 return (Panel B). The key independent variable *Day* is an indicator for the treading day relative to the PPP loan return announcement date, *Day 0* (e.g., 8-K filing, press release). The time period is from Day -60 to Day 1. The estimation window for the market model is Day -270 to Day -61. The day count excludes non-trading days (e.g., weekends, holidays). Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles. Standard errors are clustered at the trading day level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. t-statistics are presented in parentheses.

	Panel A: Market-adjusted			Panel B: Market model		
	Day -1	Day 0	Day +1	Day -1	Day 0	Day +1
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All observations						
Across firms						
Abnormal return	-0.00662	0.0256***	0.00395	-0.00742	0.0263***	0.00409
t-statistic	(-1.08)	(3.23)	(0.56)	(-1.15)	(3.23)	(0.56)
Within firms						
Abnormal return	-0.00659	0.0256***	0.00386	-0.00740	0.0263***	0.00410
t-statistic	(-1.05)	(3.32)	(0.54)	(-1.12)	(3.35)	(0.56)
Panel B: Only 8-K filings						
Across firms						
Abnormal return	-0.00983	0.0294***	0.00273	-0.0116	0.0308***	0.00162
t-statistic	(-1.29)	(2.97)	(0.34)	(-1.46)	(3.04)	(0.18)
Within firms						
Abnormal return	-0.00983	0.0294***	0.00273	-0.0116	0.0308***	0.00162
t-statistic	(-1.25)	(3.12)	(0.33)	(-1.42)	(3.22)	(0.18)
Panel C: Only 8-K filings & non-penny stocks						
Across firms						
Abnormal return	-0.0108	0.0281***	0.00455	-0.0132	0.0300***	0.00384
t-statistic	(-1.35)	(2.67)	(0.35)	(-1.48)	(2.68)	(0.28)
Within firms						
Abnormal return	-0.0108	0.0281***	0.00455	-0.0132	0.0300***	0.00384
t-statistic	(-1.28)	(2.72)	(0.35)	(-1.43)	(2.71)	(0.29)

Table 15
PPP loan return, loan size, and $2M loan size cutoff

This table reports the results from a linear probability (OLS) model where the dependent variable is an indicator for public company returning a PPP loan to the SBA and independent variables are the natural logarithm of PPP loan amount, an indicator for loan amount above $2 million, and company characteristics. Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles. Standard errors are clustered at the industry level, defined as 2-digit NAICS, where we combine industries with few PPP-eligible companies into one bucket. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. t-statistics are presented in parentheses.

	Dependent variable = PPP Loan Returner (1/0)		
	(1)	(2)	(3)
Log (PPP Loan Amount)	0.0751***	0.0489**	0.0449
	(7.22)	(2.74)	(1.63)
Above $2M (1/0)		0.0885*	0.00473
		(1.82)	(0.08)
Log (PPP Loan Amount)^2			0.0208**
			(2.76)
Firm Characteristics	No	No	Yes
Penny Stock Dummy	No	No	Yes
Industry Dummies	No	No	Yes
Returns Controls	No	No	Yes
# obs.	568	568	534
Adjusted R^2	0.0600	0.0628	0.127

Internet Appendix to "Small Bank Financing and Funding Hesitancy in a Crisis: Evidence from the Paycheck Protection Program"

NOT FOR PUBLICATION

Section IA.A: Supplementary Graphs and Tables

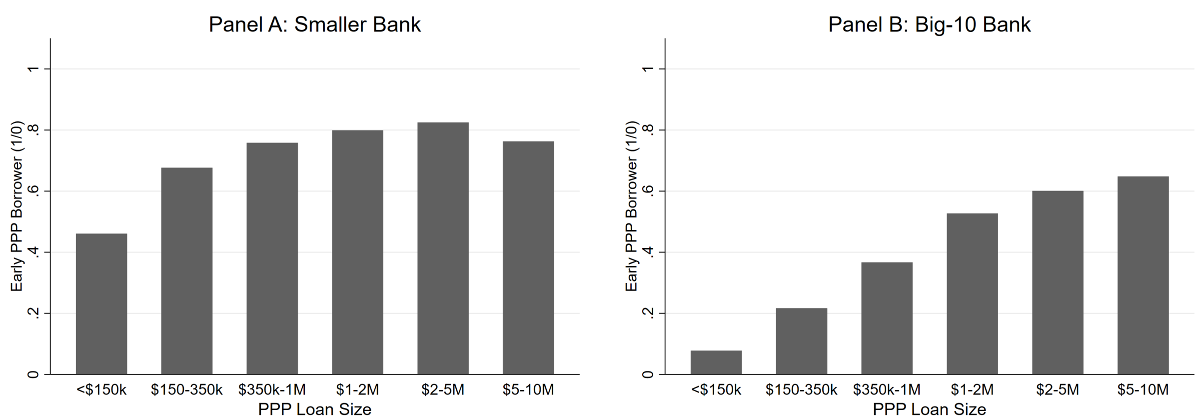

Figure IA.1. Probability of early PPP borrowing: small versus big banks – Full SBA data. This figure plots the probability of borrowing early (i.e., in PPP Round 1) versus borrowing late (i.e., in PPP Round 2) for PPP borrowers from the SBA's PPP data release in December 2020, which we restrict to non-financial corporations, for comparability, by PPP loan size bin. Panel A reports the results for smaller (non-big-10) banks, with this category including non-bank lenders. Excluding non-bank lenders does not affect the results. Panel B reports the results for big-10 banks.

Table IA.1
Matching statistics: DealScan and UCC

Columns (1) to (3) report the mean, median, and standard deviation of several financial characteristics of firms that we were able to match to DealScan. Columns (4) to (6) report the same statistics for firms that we were able to match to UCC and Columns (7) to (9) report the same statistics for unmatched firms. In the case of discrete variables, the statistics are proportions. Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles.

	Matched to DealScan (N=231)			Matched to UCC (N=301)			Unmatched (N=277)		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Firm size									
PPP Loan Amount ($ million)	4.106	2.651	3.834	3.278	1.900	3.527	1.233	0.564	1.844
Book Value of Assets ($ million)	154.5	62.1	209.7	116.0	48.9	182.8	45.8	17.6	78.1
Market Cap ($ million)	119.1	41.9	206.1	126.1	39.7	220.9	65.4	31.5	98.6
Sales ($ million)	136.8	65.4	183.9	103.8	34.5	170.5	29.5	6.2	82.4
# Employees ('000)	0.629	0.230	1.178	0.456	0.150	0.977	0.097	0.042	0.159
Panel B: Other financial characteristics									
Firm Age (years)	22.846	23.000	13.631	16.936	13.000	13.791	10.681	7.500	10.105
Book Equity <0 (1/0)	15.0%	—	—	20.7%	—	—	27.6%	—	—
Tobin's Q	1.252	1.066	1.204	1.614	1.128	1.847	1.847	1.177	2.311
Sales Growth	0.154	-0.011	1.710	0.316	0.026	1.779	1.289	0.036	5.477
Dividend Payer (1/0)	22.0%	—	—	14.2%	—	—	10.0%	—	—
Current Ratio	2.330	1.683	2.078	2.381	1.662	2.279	2.761	1.712	3.134
Cash/Non-Cash Assets	0.484	0.104	1.555	0.833	0.163	2.161	1.360	0.383	2.338
Free Cash Flow/Assets	0.098	0.029	0.442	0.099	0.033	0.608	0.259	0.040	1.086
Panel C: Financial constraints									
Has Credit Rating (1/0)	7.4%	—	—	5.0%	—	—	0.4%	—	—
WW Index $\geq$ p75 (1/0)	60.5%	—	—	66.5%	—	—	79.7%	—	—
SA Index $\geq$ p75 (1/0)	51.8%	—	—	70.5%	—	—	93.5%	—	—
Panel D: Leverage and distress									
Zero Debt (1/0)	9.3%	—	—	7.5%	—	—	10.0%	—	—
Market Leverage	0.326	0.278	0.264	0.304	0.245	0.267	0.186	0.100	0.227
Interest Coverage <1.5 (1/0)	67.6%	—	—	77.1%	—	—	86.4%	—	—
Altman Z-score <1.81 (1/0)	56.4%	—	—	66.4%	—	—	78.3%	—	—
Distance-to-Default	2.676	2.370	1.840	2.632	2.305	2.019	2.703	2.054	1.963
Penny Stock (1/0)	65.4%	—	—	72.7%	—	—	83.9%	—	—
Panel E: Stock returns									
Covid Period Return	-0.331	-0.408	0.408	-0.326	-0.398	0.391	-0.280	-0.371	0.466
Stimulus Day Return	0.066	0.052	0.110	0.066	0.057	0.121	0.044	0.016	0.131
PPP Grant Abnormal Return	0.016	0.002	0.108	0.022	0.006	0.122	0.028	0.004	0.135

Table IA.2
Early PPP access and lender effects

This table reports the results from a multinomial logit model for public PPP recipients where the dependent variable is a categorical variable for the intersection between a bank type (big-10 bank versus smaller bank) and borrower type (early versus late PPP borrower). The independent variable is firm size (Panel A) and the PPP loan size (Panel B). The dependent variable *Bank Type–Borrower Type Category (Y)* takes the value of 3 for smaller (non-big-10) bank and early PPP borrower, 2 for smaller bank and late PPP borrower, 1 for big-10 bank and early PPP borrower, and 0 for big-10 bank and late PPP borrower. We classify the following banks as big-10 banks: JPMorgan Chase Bank, Wells Fargo Bank, Bank of America, Citibank, U.S. Bank, Truist Bank, PNC Bank, Bank of New York, State Street Corporation, and TD Bank. An early borrower is a public company receiving a PPP loan before April 17, 2020. Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles. Standard errors are clustered at the industry level, defined as 2-digit NAICS, where we combine industries with few PPP-eligible companies into one bucket. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. z-statistics are presented in parentheses. Constants are omitted for brevity.

	Dependent variable = Bank Type–Borrower Type Category (Y)			
	Predictor	Coefficient	Relative risk ratio	z-statistic
	(1)	(2)	(3)	(4)
Panel A: Firm size				
Y = 3: Smaller Bank–Early PPP Borrower	Log (Assets)	-0.196***	0.82	(-3.08)
Y = 2: Smaller Bank–Late PPP Borrower	Log (Assets)	-0.364***	0.69	(-5.63)
Y = 1: Big-10 Bank–Early PPP Borrower	[Base outcome]	—	—	—
Y = 0: Big-10 Bank–Late PPP Borrower	Log (Assets)	-0.448***	0.64	(-4.37)
# obs.	525			
Pseudo-R^2	0.0185			
Log-likelihood	-615.6			
Panel B: PPP loan size				
Y = 3: Smaller Bank–Early PPP Borrower	Log (PPP Loan Amount)	-0.233**	0.79	(-2.41)
Y = 2: Smaller Bank–Late PPP Borrower	Log (PPP Loan Amount)	-0.412***	0.66	(-3.10)
Y = 1: Big-10 Bank–Early PPP Borrower	[Base outcome]	—	—	—
Y = 0: Big-10 Bank–Late PPP Borrower	Log (PPP Loan Amount)	-0.554***	0.57	(-3.75)
# obs.	525			
Pseudo-R^2	0.0172			
Log-likelihood	-616.5			

Table IA.3
Early PPP access and lender effects
Bank relationship

This table reports the results from a multinomial logit model for public PPP recipients where the dependent variable is a categorical variable for the intersection between a bank type (big-10 bank versus smaller bank) and borrower type (early versus late PPP borrower), for a subsample of publicly listed firms with prior bank relationships (i.e., before the PPP). The independent variable is firm size (Panel A) and the PPP loan size (Panel B). The dependent variable *Bank Type–Borrower Type Category (Y)* takes the value of 3 for smaller (non-big-10) bank and early PPP borrower, 2 for smaller bank and late PPP borrower, 1 for big-10 bank and early PPP borrower, and 0 for big-10 bank and late PPP borrower. We classify the following banks as big-10 banks: JPMorgan Chase Bank, Wells Fargo Bank, Bank of America, Citibank, U.S. Bank, Truist Bank, PNC Bank, Bank of New York, State Street Corporation, and TD Bank. An early borrower is a public company receiving a PPP loan before April 17, 2020. Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles. Standard errors are clustered at the industry level, defined as 2-digit NAICS, where we combine industries with few PPP-eligible companies into one bucket. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. z-statistics are presented in parentheses. Constants are omitted for brevity.

	Dependent variable = Bank Type–Borrower Type Category (Y)			
	Predictor	Coefficient	Relative risk ratio	z-statistic
	(1)	(2)	(3)	(4)
Panel A: Firm size				
Y = 3: Smaller Bank–Early PPP Borrower	Log (Assets)	-0.497***	0.61	(-3.07)
Y = 2: Smaller Bank–Late PPP Borrower	Log (Assets)	-0.384**	0.68	(-1.99)
Y = 1: Big-10 Bank–Early PPP Borrower	[Base outcome]	—	—	—
Y = 0: Big-10 Bank–Late PPP Borrower	Log (Assets)	-0.364**	0.69	(-2.20)
# obs.	173			
Pseudo-R^2	0.0253			
Log-likelihood	-198.2			
Panel B: PPP loan size				
Y = 3: Smaller Bank–Early PPP Borrower	Log (PPP Loan Amount)	-0.750***	0.47	(-4.36)
Y = 2: Smaller Bank–Late PPP Borrower	Log (PPP Loan Amount)	-0.588***	0.56	(-2.98)
Y = 1: Big-10 Bank–Early PPP Borrower	[Base outcome]	—	—	—
Y = 0: Big-10 Bank–Late PPP Borrower	Log (PPP Loan Amount)	-0.500**	0.61	(-2.23)
# obs.	173			
Pseudo-R^2	0.0328			
Log-likelihood	-196.7			

Table IA.4
Early PPP access and lender effects
No bank relationship

This table reports the results from a multinomial logit model for public PPP recipients where the dependent variable is a categorical variable for the intersection between a bank type (big-10 bank versus smaller bank) and borrower type (early versus late PPP borrower), for a subsample of publicly listed firms without prior bank relationships (i.e., before the PPP). The independent variable is firm size (Panel A) and the PPP loan size (Panel B). The dependent variable *Bank Type–Borrower Type Category (Y)* takes the value of 3 for smaller (non-big-10) bank and early PPP borrower, 2 for smaller bank and late PPP borrower, 1 for big-10 bank and early PPP borrower, and 0 for big-10 bank and late PPP borrower. We classify the following banks as big-10 banks: JPMorgan Chase Bank, Wells Fargo Bank, Bank of America, Citibank, U.S. Bank, Truist Bank, PNC Bank, Bank of New York, State Street Corporation, and TD Bank. An early borrower is a public company receiving a PPP loan before April 17, 2020. Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles. Standard errors are clustered at the industry level, defined as 2-digit NAICS, where we combine industries with few PPP-eligible companies into one bucket. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. z-statistics are presented in parentheses. Constants are omitted for brevity.

	Dependent variable = Bank Type–Borrower Type Category (Y)			
	Predictor	Coefficient	Relative risk ratio	z-statistic
	(1)	(2)	(3)	(4)
	Panel A: Firm size			
Y = 3: Smaller Bank–Early PPP Borrower	Log (Assets)	-0.0409	0.96	(-0.52)
Y = 2: Smaller Bank–Late PPP Borrower	Log (Assets)	-0.393***	0.68	(-4.79)
Y = 1: Big-10 Bank–Early PPP Borrower	[Base outcome]	—	—	—
Y = 0: Big-10 Bank–Late PPP Borrower	Log (Assets)	-0.425***	0.65	(-6.47)
# obs.	352			
Pseudo-R^2	0.0289			
Log-likelihood	-409.6			
	Panel B: PPP loan size			
Y = 3: Smaller Bank–Early PPP Borrower	Log (PPP Loan Amount)	-0.00414	1.00	(-0.08)
Y = 2: Smaller Bank–Late PPP Borrower	Log (PPP Loan Amount)	-0.428***	0.65	(-6.21)
Y = 1: Big-10 Bank–Early PPP Borrower	[Base outcome]	—	—	—
Y = 0: Big-10 Bank–Late PPP Borrower	Log (PPP Loan Amount)	-0.526***	0.59	(-3.80)
# obs.	352			
Pseudo-R^2	0.0273			
Log-likelihood	-410.3			

Table IA.5
Early PPP access, lender effects, and bank relationships: SBA PPP data

This table reports the results from a multinomial logit model based on SBA PPP data and UCC–SBA PPP data where the dependent variable is a categorical variable for the intersection between a bank type (big-10 bank versus smaller bank) and borrower type (early versus late PPP borrower). The independent variable *Log (PPP Loan Size)* is the natural logarithm of the PPP loan size from the SBA's PPP data release in December 2020, which we restrict to non-financial corporations, for comparability. The dependent variable *Bank Type–Borrower Type Category (Y)* takes the value of 3 for smaller (non-big-10) bank and early PPP borrower, 2 for smaller bank and late PPP borrower, 1 for big-10 bank and early PPP borrower, and 0 for big-10 bank and late PPP borrower. We classify the following banks as big-10 banks: JPMorgan Chase Bank, Wells Fargo Bank, Bank of America, Citibank, U.S. Bank, Truist Bank, PNC Bank, Bank of New York, State Street Corporation, and TD Bank. An early borrower is a public company receiving a PPP loan before April 17, 2020. Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles. Standard errors are clustered at the industry level, defined as 2-digit NAICS, where we combine industries with few PPP-eligible companies into one bucket. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. z-statistics are presented in parentheses. Constants are omitted for brevity.

	Dependent variable = Bank Type–Borrower Type Category (Y)			
	Predictor	Coefficient	Relative risk ratio	z-statistic
	(1)	(2)	(3)	(4)
Panel A: All firms				
Y = 3: Smaller Bank–Early PPP Borrower	Log (PPP Loan Size)	-0.167***	0.85	(-7.77)
Y = 2: Smaller Bank–Late PPP Borrower	Log (PPP Loan Size)	-0.601***	0.55	(-19.03)
Y = 1: Big-10 Bank–Early PPP Borrower	[Base outcome]	—	—	—
Y = 0: Big-10 Bank–Late PPP Borrower	Log (PPP Loan Size)	-0.635***	0.53	(-27.00)
# obs.	554,422			
Pseudo-R^2	0.0390			
Log-likelihood	-626379			
Panel B: Bank relationship				
Y = 3: Smaller Bank–Early PPP Borrower	Log (PPP Loan Size)	-0.256***	0.77	(-7.89)
Y = 2: Smaller Bank–Late PPP Borrower	Log (PPP Loan Size)	-0.634***	0.53	(-16.21)
Y = 1: Big-10 Bank–Early PPP Borrower	[Base outcome]	—	—	—
Y = 0: Big-10 Bank–Late PPP Borrower	Log (PPP Loan Size)	-0.600***	0.55	(-38.48)
# obs.	301,552			
Pseudo-R^2	0.0294			
Log-likelihood	-323917			
Panel C: No bank relationship				
Y = 3: Smaller Bank–Early PPP Borrower	Log (PPP Loan Size)	-0.103***	0.90	(-4.33)
Y = 2: Smaller Bank–Late PPP Borrower	Log (PPP Loan Size)	-0.515***	0.60	(-14.52)
Y = 1: Big-10 Bank–Early PPP Borrower	[Base outcome]	—	—	—
Y = 0: Big-10 Bank–Late PPP Borrower	Log (PPP Loan Size)	-0.549***	0.58	(-24.88)
# obs.	252,870			
Pseudo-R^2	0.0284			
Log-likelihood	-296605			

Table IA.6
Financial constraints, solvency, and PPP loan return

This table reports the results from a linear probability (OLS) model where the dependent variable is an indicator for public company returning a PPP loan to the SBA and independent variables are financial constraints and solvency indexes. Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles. Standard errors are clustered at the industry level, defined as 2-digit NAICS, where we combine industries with few PPP-eligible companies into one bucket. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. t-statistics are presented in parentheses.

	Dependent variable = PPP Loan Returner (1/0)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
WW Index	-0.142***	-0.138***	-0.137***						
$\geq$ p75 (1/0)	(-3.72)	(-3.85)	(-3.38)						
SA Index				-0.111***	-0.123***	-0.113**			
$\geq$ p75 (1/0)				(-3.27)	(-3.31)	(-2.71)			
Altman Z-score							-0.097***	-0.109***	-0.111***
<1.81 (1/0)							(-3.42)	(-3.29)	(-3.46)
Penny Stock Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummies	—	Yes	Yes	—	Yes	Yes	—	Yes	Yes
Returns Controls	—	—	Yes	—	—	Yes	—	—	Yes
# obs.	400	400	394	519	519	511	479	479	472
Adjusted R^2	0.0716	0.0920	0.0910	0.0587	0.0754	0.0753	0.0720	0.0934	0.0962

Table IA.7
PPP loan return propensity and distance to default

This table reports the results from a linear probability (OLS) model where the dependent variable is an indicator for public company returning a PPP loan to the SBA and independent variables are *Distance-to-Default* and other company characteristics. Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles. Standard errors are clustered at the industry level, defined as 2-digit NAICS, where we combine industries with few PPP-eligible companies into one bucket. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. *t*-statistics are presented in parentheses.

	Dependent variable = PPP Loan Returner (1/0)		
	(1)	(2)	(3)
Distance-to-Default	0.0549***	0.0617***	0.0633***
	(4.93)	(4.62)	(4.79)
Log (Assets)	0.0872***	0.0901***	0.0970***
	(4.21)	(3.66)	(3.48)
Log (Age)	-0.0270	-0.0150	-0.0199
	(-1.71)	(-1.00)	(-1.25)
Book Equity <0 (1/0)	0.0331	0.0104	0.0286
	(0.46)	(0.21)	(0.50)
Tobin's Q	0.00776	0.00141	0.00313
	(0.49)	(0.11)	(0.31)
Current Ratio	0.00669	0.00361	0.00287
	(1.32)	(0.73)	(0.62)
Cash/Non-Cash Assets	0.00239	-0.00107	-0.000491
	(0.20)	(-0.09)	(-0.05)
Penny Stock (1/0)	-0.00524	-0.0101	-0.0893
	(-0.10)	(-0.19)	(-0.73)
Covid Industry (1/0)		-0.0362	-0.0408
		(-0.99)	(-0.99)
Machinery Industry (1/0)		-0.0896**	-0.0908
		(-2.26)	(-1.76)
Health Industry (1/0)		0.153***	0.132***
		(3.03)	(3.41)
High-Tech Industry (1/0)		-0.0211	-0.0186
		(-0.67)	(-0.48)
Covid Period Return			0.169
			(1.13)
Covid Period Return × Penny Stock (1/0)			-0.0802
			(-0.41)
Stimulus Day Return			-0.713**
			(-2.71)
Stimulus Day Return × Penny Stock (1/0)			0.615*
			(1.98)
PPP Grant Abnormal Return			0.645
			(1.28)
PPP Grant Abnormal Return × Penny Stock (1/0)			-0.697
			(-1.06)
# obs.	383	383	382
Adjusted R^2	0.140	0.162	0.166

Section IA.B: Industry Clusters for Estimating Application Probability

We create the following four industry clusters for estimating application probability:

- *Covid Impacted Industries:* These firms are in industries negatively impacted by Covid-19 pandemic (Fahlenbrach et al. (2020)) and may be more likely to apply for PPP funding.
- *Health Sector:* We identify these as firms in Fama-French 49 industries 11, 12, and 13, respectively. Firms in these sector may experience growth opportunities that increase funding demand. On the other hand, availability of private capital may deter PPP application as it raises the probability of a negative finding of ineligibility. This may be a concern for these firms as many are supervised by government agencies and apply for government grants.
- *High Tech Sector:* We identify these as firms with Fama-French-49 industry codes of 35, 36, or 37. The firms may see growth opportunities from changes in work habits that result in greater demand for technology. They may also be better able to function remotely than (say) a meatpacking plant. These factors may push the firms to seek PPP funding.
- *Machinery Sector:* This includes "heavy industry" firms with Fama-French-49 industry code = 21 (usually NAICS-2 = 33). These firms have more rigidity on the real side and may thus have greater demand for short-term liquidity.

Figure 11, Panel B shows that our industry clusters pick up significant variation in PPP application patterns. 64.8% of the 176 firms in Covid-19 industries apply for PPP, about double the full-sample application probability of 31.96%. In the machinery sector, 16 out of 37 firms (43.2%) apply, again higher than the baseline odds. The application probability is lower in the health sector, where 191 out of 805 firms apply for PPP loans (23.7%). We find that 112 out of 255 high tech firms (43.9%) apply for PPP funding, again higher than the baseline of around 39%.

Section IA.C: Evidence of PPP Scrutiny Concerns

Quotes from EDGAR filings

- Albert Bourla, Pfizer CEO: "Pfizer made it a point to not accept government funding. ... to liberate our scientists from any bureaucracy that could come from accepting money."
- Adamis Pharmaceuticals 8-K filing: "... Such audit or review could result in the diversion of management's time and attention and legal and reputational costs."
- Nature's Sunshine Products 8-K filing: "... civil, criminal, and administrative penalties ... adverse publicity, damage to reputation ... consume significant financial and management resources."

PPP Loan Necessity Questionnaire (Form #3509)

Subjective questions, assessment based on "... totality of circumstances."[1]

- *... Has Borrower voluntarily ceased, reduced, or altered its operations? [Why? in 1000 characters or less]*
- *Did Borrower begin any new capital improvement projects not due to COVID-19? [Comments in 1000 characters or less]*
- *Has borrower paid dividends, prepaid debt, paid any employees $250K, was 20% owned by public companies ... ?*

[1] See, e.g., *New Uncertainty About the Uncertainty Certifiction: SBA's Draft Questionnaires for PPP Loans Over $2 Million*, Daily Tax Report, November 4, 2020.

Section IA.D: Definitions of Variables

Variable	Definition	Source	Formula
PPP borrowing			
Early PPP Borrower (1/0)	Dummy for early PPP borrower versus late borrower, defined based on SBA approval date, loan grant date, or contract date (in that order)	EDGAR, SBA	=1 if approved or borrowed before April 27, 2020, 0 o/w
PPP Borrower (1/0)	Dummy for PPP borrower versus public PPP-eligible non-borrower	EDGAR	=1 if borrower, 0 o/w
PPP Loan Returner (1/0)	Dummy for PPP loan returner versus PPP loan retainer	EDGAR	=1 if loan returned, 0 o/w
PPP Loan Amount ($ million)	Aggregate PPP loan amount per EDGAR filer, measured in $ million	EDGAR	=ppp_size
PPP Loan Size ($ million)	PPP loan amount per SBA PPP recipient, measured in $ million	SBA PPP data (Dec)	=loanamount
Above $2M (1/0)	Dummy for PPP loan size of $2 million or above	EDGAR	=(ppp_size$\geq$2)
Big-10 Bank (1/0)	Dummy for PPP lender being a big-10 bank, that is, JPMorgan Chase Bank, Wells Fargo Bank, Bank of America, Citibank, U.S. Bank, Truist Bank, PNC Bank, Bank of New York, State Street Corporation, or TD Bank	Call reports	=1 if big_bank=1, 0 o/w
Smaller Bank (1/0)	Dummy for PPP lender being a non-big-10 bank; see Big-10 Bank (1/0)	Call reports	=1 if big_bank=0, 0 o/w
Bank Type–Borrower Type Category	Categorical variable for the intersection between a bank type (big-10 bank versus smaller bank) and borrower type (early versus late PPP borrower)	EDGAR, Call reports	= 3 if big_bank=1 & early=1; 2 if big_bank=1 & early=0; 1 if big_bank=0 & early=1; 0 if big_bank=0 & early=0
Bank Relationship (1/0)	Dummy for the firm obtaining a secured loan from a bank in 2015–2019	UCC	=1 if securedpartyname is bank, 0 o/w
Relationship Bank PPP (1/0)	Dummy for the firm obtaining a secured loan from its PPP lender in 2015–2019	UCC	=1 if lender= securedpartyname, 0 o/w
Small Bank Relationship (1/0)	Dummy for the firm obtaining a secured loan from a small (non-big-10) bank in 2015–2019	UCC, Call reports	=1 if securedpartyname!= big_bank, 0 o/w
Firm size			
Book Value of Assets ($ million)	Assets, measured in $ million	Compustat	=at
Market Cap ($ million)	Market Capitalization, measured in $ million	Compustat	=prcc_f*csho
Sales ($ million)	Sales, measured in $ million	Compustat	= sale
# Employees ('000)	Employees, measured in thousand	Compustat	=emp, set to 2018 if N/A
Other financial characteristics			
Firm Age (years)	Years since IPO, capped at 37 years	Compustat	=fyear-min(fyear) if prcc_f!=., 0 if missing
Book Equity <0	Dummy for negative Book Equity defined as in Fama-French: BE = book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit (if available), minus the book value of preferred stock	Compustat	=(seq OR ceq+pstk OR at-lt, in that order) +(txditc OR txdb+itcb, where each is set to 0 if missing OR 0, in that order) +(pstkrv OR pstkl OR pstk, in that order)
Tobin's Q	Market Value of Assets/Assets	Compustat	=(at+prcc_f*csho-ceq)/at, set to 0 if ceq<0 or if missing
Sales Growth	Year-on-year sales growth	Compustat	=(sale-sale[_n-1])/sale[_n-1]
Dividend Payer (1/0)	Dummy for dividend payer	Compustat	=(dv>0) if dv!=.
Current Ratio	Current Assets/Current Liabilities	Compustat	=act/lct
Cash/Non-Cash Assets	Cash/(Assets-Cash)	Compustat	=che/(at-che), where at is in thousands
Free Cash Flow/Assets	(Operating Cash Flow - Extraordinary Items + Interest Paid - Interest Expense*((Pretax Income - Net Income)/Pretax Income) - CapEx)/Assets	Compustat	=(oancf-xidoc+intpn-xint*((pi-ni)/pi)-capx)/at
Financial constraints			
Has Credit Rating (1/0)	Dummy for company having a long-term S&P credit rating or a Mergent rating for an issue with maturity of at least three years	S&P, Mergent	=1 if rated, 0 o/w

Variable	Definition		
WW Index ≥ p75 (1/0)	Dummy for WW (Whited and Wu) Index in 4th (upper) quartile of *all* public firms, where WW Index is calculated as -0.737*Ln of Min(Assets,4500) + 0.043*Squared Ln of Min(Assets,4500) – 0.040*Min(Years since IPO,37)	Compustat	=(WW_quart==4) if WW_quart!=., using xtile, where WW=-0.737*log(min(at,4500)) +0.043*(log(min(at,4500)))^2 -0.040*min(age,37)
SA Index ≥ p75 (1/0)	Dummy for SA (Hadlock and Pierce) Index in 4th quartile of *all* public firms, where SA Index is -0.737*Ln of Min(Assets,4500) +0.043*Squared Ln of Min(Assets,4500) -0.040*Min(Years since IPO,37)	Compustat	=(SA_quart==4) if SA_quart!=., using xtile, where SA=-0.737*log(min(at,4500)) +0.043*(log(min(at,4500)))^2 -0.040*min(age,37)
Leverage and distress			
Zero Debt (1/0)	Dummy for zero debt	Compustat	=1 if dlc+dltt=0 or (dltt=. & dlc=0), 0 o/w
Market Leverage	(Short-Term Debt + Long-Term Debt)/(Debt + Market Cap)	Compustat	=(dlc+dltt)/ (dlc+dltt+prcc_f*csho)
Interest Coverage <1.5 (1/0)	Dummy for 1 + Pretax Income/Interest Expense <1.5	Compustat	=((1+pi/xint)<1.5) if (1+pi/xint)!=.
Altman Z-score < 1.81 (1/0)	Dummy for Altman Z-score <1.81, wehere Z-score is calculated as 1.2*Working Capital/Assets + 1.4*Retained Earnings/Assets + 3.3*EBIT/Assets + 0.6*Market Cap/Liabilities + 0.999*Sales/Assets	Compustat	=1 if Z-score <1.81, 0 o/w, where Z-score= 1.2*(act-lct)/at +1.4*re/at +3.3*(pi+xint+dp-dp)/at+.6*prcc_f*csho/lt +.999*sale/at
Distance-to-Default	Distance-to-default from NUS RMI Credit Research Initiative	NUS RMI	= dtd
Penny Stock (1/0)	Dummy for company's stock price below $5 based on (1) closing stock price as of fiscal year-end for cross-sectional tests or (2) average stock price in December 2019 for event study analysis	Compustat	=(prcc_f<5) if prcc_f!=. OR mean(p_adjclose, Dec 2019)<5
Industry composition			
Covid Industry (1/0)	Dummy for Covid-19 Affected Industry	Compustat	=1 if sic corresponds to Covid-19 industry, 0 o/w
Machinery Industry (1/0)	Dummy for Machinery Industry	Compustat	=1 if sic corresponds to FF49==21, 0 o/w
Health Industry (1/0)	Dummy for Health, Pharma, and Biotech Industry	Compustat	=1 if sic corresponds to FF49==11,12,13, 0 o/w
High-Tech industry (1/0)	Dummy for Business Equipment – Computers, Software, and Electronic Equipment Industry	Compustat	=1 if sic corresponds to FF49==35,36,37, 0 o/w
Returns and event study variables			
Buy-and-Hold Abnormal Return	Cumulative return on the stock over the S&P 500 return from January 1, 2020 to August 15, 2020, adjusted for stock splits and dividends	Yahoo! Finance	=cumulative (R_adjclose - S&P 500 R_adjclose)
Covid Period Return	Cumulative stock return from February 2, 2020 to March 23, 2020, adjusted for stock splits and dividends	Yahoo! Finance	=cumulative R_adjclose, Covid period
Stimulus Day Return	Stock return on March 24, 2020, adjusted for stock splits and dividends	Yahoo! Finance	=R_adjclose, Mar 24, 2020
Abnormal Return	Company's (1) market-adjusted return (stock return minus S&P 500 return) or (2) market model return (based on S&P 500), adjusted for stock splits and dividends	Yahoo! Finance	=R_adjclose - S&P 500 R_adjclose OR Abnormal R_adjclose
Day -1 (1/0)	Trading day preceding (1) PPP loan grant announcement day or (2) PPP loan return announcement day, as appropriate	EDGAR	=(evday==-1) OR (evday1==-1)
Day 0 (1/0)	Trading day of (1) PPP loan grant announcement or (2) PPP loan return announcement, as appropriate	EDGAR	=(evday==0) OR (evday1==0)
Day +1 (1/0)	Trading day following (1) PPP loan grant announcement day or (2) PPP loan return announcement day, as appropriate	EDGAR	=(evday==1) OR (evday1==1)