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THE TARGETING AND IMPACT OF PAYCHECK PROTECTION PROGRAM LOANS TO SMALL BUSINESSES

Alexander W. Bartik
Zoe B. Cullen
Edward L. Glaeser
Michael Luca
Christopher T. Stanton
Adi Sunderam

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ABSTRACT

The Paycheck Protection Program (PPP) aimed to quickly deliver hundreds of billions of dollars of loans to small businesses, with the loans administered via private banks. In this paper, we use firm-level data to document the demand and supply of PPP funds. Using an instrumental variables approach, we find that PPP loans led to a 14 to 30 percentage point increase in a business's expected survival, and a positive but imprecise effect on employment. Moreover, the effects on survival were heterogeneous and highlight an important tradeoff faced by policymakers: while administering the loans via private banks allowed for rapid delivery of funds, it also limited the government's ability to target the funding - instead allowing pre-existing connections between businesses and banks to determine which firms would benefit from the program.

Alexander W. Bartik
University of Illinois at Urbana-Champaign
1407 W. Gregory Road
214 David Kinley Hall
Urbana, IL 61821
abartik@illinois.edu

Zoe B. Cullen
Rock Center 210
Harvard Business School
60 N. Harvard
Boston, MA 02163
zcullen@hbs.edu

Edward L. Glaeser
Department of Economics
315A Littauer Center
Harvard University
Cambridge, MA 02138
and NBER
eglaeser@harvard.edu

Michael Luca
Harvard Business School
Soldiers Field
Boston, MA 02163
and NBER
mluca@hbs.edu

Christopher T. Stanton
210 Rock Center
Harvard University
Harvard Business School
Boston, MA 02163
and NBER
christopher.t.stanton@gmail.com

Adi Sunderam
Harvard Business School
Baker Library 359
Soldiers Field
Boston, MA 02163
and NBER
asunderam@hbs.edu

I. Introduction

The COVID-19 pandemic has led to a rapid contraction in economic activity, including sharply reduced employment and widespread temporary business closures (Bartik et al 2020a). Small businesses have been particularly hard hit by the crisis, with employment during April 2020 declining over 18 percent at firms with under 50 employees, compared to only 13 percent at firms with over 1000 employees (ADP April Employment Report, 2020).

In anticipation of the economic impact of COVID-19 related disruptions, Congress created the Paycheck Protection Program (PPP) as part of the CARES Act passed on March 27, 2020. PPP allowed small and medium sized firms that certified that their businesses were "substantially affected by COVID-19 to take up uncollateralized, low-interest rate loans for up to 2.5 times monthly pre-COVID payroll – with the potential for loans to be forgiven altogether.

The scale of the stimulus package was enormous – offering $649 billion in loans across two tranches. To expedite delivery of the funds, PPP loans were guaranteed by the federal government's Small Business Administration (SBA) but administered by banks. Applications for the first tranche of PPP loans started on April 3, 2020 and included funds for $349 billion in loans - which were exhausted by April 16, 2020. The second tranche, approved in a revised bill on April 24, began being distributed on April 27, 2020 and included over $300 billion in additional funding. While administering PPP via banks allowed for rapid delivery, it also reduced the government's ability to target the funds (e.g. to businesses most in need, or to businesses where the funds would have the largest impact). Instead, program take-up was largely left to bank decisions, especially during the first tranche when there was considerable excess demand for funding.

In this paper, we investigate the take-up and impact of first-tranche PPP loans, using surveys of small businesses conducted via Alignable between April 25 and April 27. Ninety percent of these survey responses were collected prior to the first day of the second tranche of PPP funding, at a time when access to loans was restricted. We evaluate the allocation of funds from the first-tranche using a model where the social planner trades off the speed of loan delivery with the effectiveness of loan targeting.

How did banks allocate PPP funds? We find that businesses that were more impacted by COVID-related disruptions were more likely to seek funds. Businesses with less cash on hand, businesses in more affected industries, and businesses reporting more distress due to the crisis were markedly more likely to apply for PPP loans. However, these applications from distressed businesses were less likely to be approved. Although, more affected businesses were less likely to receive PPP loans during the first tranche, to evaluate whether this allocation of loans was suboptimal we must discern whether the impact of PPP funding differed for these businesses relative to less affected businesses.

We first estimate the causal impact of PPP on business survival and employment, on average, before turning to treatment effect heterogeneity. To address the endogeneity of PPP approval decisions, we instrument for approval using information about pre-existing banking relationships of businesses. We use the fact that individual banks varied in their approval rates, with the largest banks having lower approval rates. Specifically, among the top 20 banks by size in the U.S., we find that the top 4 had the lowest PPP approval rates, followed by the top 5-10. These differences in approval rates likely reflect operational challenges in administering the program as borrowers rushed to apply, but they may also reflect intentional choices made by the very largest banks to focus on certain clients first.[2] Restricting the sample to firms that bank with top 20 banks, we use dummies to indicating which group of banks the firm uses as an instrument for PPP approval. The exclusion restriction for these instruments boils down to the assumption that firms using large banks are similar except for the bank's handling of PPP. Similarly, among smaller financial institutions, credit unions had lower approval rates than community banks, likely because many credit unions did not have pre-existing relationships with the SBA. In a second specification, we restrict the sample to firms that bank with community banks or credit unions, and use business owners' past affiliation with a credit union as an instrument for PPP approval. The exclusion restriction in this case boils down to the assumption that small firms using credit unions are similar to those using community banks.

Using these different versions of our bank instrument and a variety of controls, we consistently find that PPP approval during the first-tranche was associated with an increase in self-reported firm survival probability of 14 to 30 percentage points. PPP approval is also estimated to increase employment, but the employment estimates are imprecise and more sensitive to the particular instrument and controls used. To corroborate our main results and shed light on realized closure rates, we conducted a phone survey in July. Specifically, we called businesses to see if

[2] https://www.nytimes.com/2020/04/22/business/sba-loans-ppp-coronavirus.html

they were open. The results are consistent with our main analysis, suggesting that PPP funding ultimately led to fewer businesses closing.

Finally, we explore heterogeneity in treatment effects by different firm characteristics to test if banks targeted PPP funds based on the efficacy of the loan for business survival. Along some dimensions, such as firms' self-reports of the pandemic's impact and remaining cash-on-hand, approval likelihoods were lower than average despite these firms having high individual-level treatment benefits from receiving PPP funding. Along other dimensions, most notably payroll size, the businesses approved for funding did have higher estimated treatment effects. This sheds light on the implications of delegating lending decisions to banks, rather than having the government pick recipients. Loans were delivered very rapidly and were well-targeted on some but not all dimensions. Some banks seem to have favored firms with closer relationships to the bank, rather than those in greater distress or with higher treatment effects. On balance, banks' targeting appears to do better than random allocation of the loans; designing programs with rules for better targeting may have resulted in further delay in getting funds to needy businesses.

This paper contributes to a growing literature studying the effects of the CARES act provisions. Recent research has studied the effects of PPP loans, exploiting variation in PPP loan receipt intensity between firms of different sizes (Chetty et al. 2020, Autor et al. 2020) and locations (Granja et al. 2020, and Bartik et al. 2020c). Employment effects are generally positive in these other papers, but they tend to be modest. To our knowledge, our paper is the first to leverage individual firm-bank relationships to understand the targeting and effectiveness of PPP loans. This enables a clearer picture of which firms were most likely to apply for, receive, and benefit from PPP loans, shedding light on how this new program may interact with an established literature on financial constraints (Myers and Majluf 1984, Holmstrom and Tirole 1997, Fazzari et al. 1988, Kaplan and Zingales 1997). Relative to complementary work, we are also able to quantify changes in firms' expectations about survival and resilience, providing important context for the long-run effects of PPP if improved balance sheets allow firms to better weather the COVID-19 crisis.

The paper proceeds as follows. The next section describes the history of the CARES act and the design of the Paycheck Protection Program. We then introduce a theoretical framework of public crisis-lending that illuminates the tradeoffs the government faces in deciding whether to delegate loan delivery or not between providing loans quickly or targeting loans to those firms' that have the highest social benefit from receiving the loans. The fourth section describes the survey data we use from Alignable. In Sections 5-6, we present results on the characteristics of firms who applied for and received PPP loans. Section 7 then presents estimates of the causal effect of PPP loans on firm reported survival probabilities and employment. Section 8 concludes and discusses the implications of our results for public crisis-lending.

II. The Paycheck Protection Program and the CARES Act

The Coronavirus Aid, Relief, and Economic Security Act, or CARES Act, is essentially unique in its combination of expeditious enactment, vast size, and unanimous support. The Congressional Budget Office estimated that it would add $1.7 trillion to the U.S. deficit, and yet the Senate passed it unanimously.[3] We will focus on one particular component of the CARES Act – the Paycheck Protection Program of PPP – but here we briefly summarize the history of the overall act and its successor.

As of March 7, 2020, there were only 275 diagnosed COVID-19 cases in the United States. Almost 2,000 were diagnosed between March 7 and March 14. Another 1,992 tests came back positive on March 15 and March 16. On March 17, cities in the San Francisco Bay Area started issuing shelter-in-place orders. March 17, 18 and 19 turned up another 10,993 cases, and on March 20, New York followed California in issuing a statewide stay-at-home order.[4]
While the American onset of the disease was remarkably rapid, observers immediately grasped that the economic impact of the pandemic could be catastrophic. Even before the first major lockdown, on March 15, the trade group Airlines for America requested $50 billion in aid.[5] On March 18, the National Restaurant Association called for $325 billion in restaurant-related aid programs,[6] but by then the Trump administration had already called on Congress to pass a one trillion dollar stimulus package. The original Treasury Department plan featured $500 billion for direct payments to taxpayers, $200 billion for distressed industries including the airlines, and $300 billion for "small business interruption loans."[7]

[3] https://www.cbo.gov/system/files/2020-04/hr748.pdf
[4] https://www.cdc.gov/coronavirus/2019-ncov/cases-updates/cases-in-us.html
[5] https://www.theguardian.com/business/2020/mar/16/us-airline-industry-seeks-50-billion-bailout-amid-coronavirus-pandemic
[6] https://restaurant.org/downloads/pdfs/business/natl-rest-association-covid-letter
[7] https://www.washingtonpost.com/context/department-of-treasury-proposal-for-coronavirus-response/6c2d2ed5-a18b-43d2-8124-28d394fa51ff/

As the economic fear spread, legislators lost any concern for fiscal restraints. Between March 4 and March 23, the Dow Jones Industrial Average dropped by 8,498 points or 31 percent of its March 4 level. The Standard and Poor's 500 Index fell by 28.5 percent over the same time period. On March 26, the Department of Labor announced that unemployment claims had increased from 282,000 during the week that ended on March 14 to 3.28 million during the week that ended on March 21. By that evening, the size of the bill had grown, and the Senate was close to a deal.

It took until Tuesday, March 24th for the Senate to agree, unanimously, on a stimulus package—the CARES Act-- that authorized over $2 trillion dollars of outlays. The bill was so popular among legislators that it had 369 co-sponsors. Hospitals and local governments together were allocated more than $250 billion and households received more than $750 billion in aid through direct payments, increased unemployment insurance, and tax deferrals.

Over $800 billion was allocated for corporate loans, which was split between the $349 billion Paycheck Protection Program (PPP), which targeted smaller businesses, and the $500 billion Exchange Stabilization Fund (ESF), which focused on larger firms.

In most industries, PPP was limited to firms with fewer than 500 employees and loans were capped at $10,000,000. The size limit of PPP to firms with under 500 employees was relaxed in some industries, most notably for industries in NAICS code 72, which includes restaurants, leisure, and hospitality, where firms are eligible for PPP as long as they had fewer than 500 employees at each location.[9] Any recipient of a PPP loan was meant to make a "good faith certification" that, among other things, acknowledged "that funds will be used to retain workers and maintain payroll or make mortgage payments, lease payments, and utility payments." Indeed, the share of the loan that was spent on payroll, mortgage, rent and utilities could be forgiven if the firm didn't reduce its number of workers. The total amount of forgiveness would decline by the percentage decline in the firm's labor force relative to a pre-crisis comparison point.[10] This $349 billion dollar program was therefore more of a grant program than a loan program.

The money was to be distributed through qualified financial intermediaries, but the procedure for allocating the $349 billion across potential lenders was far from clear. The CARES

[9] https://www.sba.gov/funding-programs/loans/coronavirus-relief-options/paycheck-protection-program
[10] https://www.govinfo.gov/content/pkg/BILLS-116hr748enr/pdf/BILLS-116hr748enr.pdf

Act endowed the Secretary of the Treasury and the Administrator of the Small Business Administration (SBA) to choose how to give the money out across banks, and in the first round of the PPP, the money was allocated through the SBA and its E-TRAN system to banks on a first-come first serve basis. The program moved precipitously fast. One banking industry official said that "banks were handed the operator's manual for a $350 billion program at 6:30 p.m." on April 2, the night before the PPP was supposed to launch.

Banks rushed to get applications into the E-TRAN system. Some of the larger banks were able to move fast. Bank of America, for example, took in 10,000 applications during the first morning of the program. Immediately, there were complaints that banks were favoring borrowers with established credit relationships. Senator Rubio, the Chair of the Small Business Committee tweeted with outrage that "BOA denied #PPP loan because they don't have a credit account," which was "A ridiculous requirement that isn't anywhere in law."

The demand for these loans was so enormous that the original $349 billion was exhausted within two weeks. Senator Rubio tweeted that "700,000 small business applications are in limbo" and #PPP will grind to a halt tonight."[11] J.P Morgan Chase reported that they had received 60,000 applications on the first day of the program, but were only able to make 27,000 loans before the money ran out.[12] This mismatch between supply and demand gave banks an extraordinary role in allocating the first round of funds.

Figure 1 displays the timing of loan approvals and fund deployment, as recorded by the SBA. The first round of the program ran out on April 16, and lending approvals stopped until April 27, after which Congress added more than $300 billion more to the program. This extra sum proved to be sufficient, since each business was only allowed a single PPP loan totaling 2.5 times their monthly payroll, and the loan remained capped at $10,000,000. Since evaluating the impact of a program that is open to all is difficult, we focus on the impact of receiving a PPP loan prior to April 24, which corresponds to the period where PPP lending was constrained by limited funds. We now turn to our model, which attempts to understand the conditions under which the PPP's structure, which includes delegating the allocation of funds to banks and a cap on loan amounts, may be optimal.

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[11] https://twitter.com/marcorubio/status/1250516086136754176

[12] https://www.nbcnews.com/business/business-news/small-business-loan-program-ran-out-money-within-minutes-some-n1187051

III. Crisis Lending: Delegation, Delay and Regulation

Large-scale public lending programs have been one major response to economic crises since the creation of the Reconstruction Finance Corporation in 1932, but rarely has a public program been as large and as unregulated as the Paycheck Protection Program. The PPP had few restrictions on who should receive the loans or the size of the loan, other than the $10 million cap and the requirement that loans be less than 2.5 times average payroll from the prior year. In this section, we consider three normative policy questions: What forces determine whether it is optimal to delegate authority over a public lending program in a largely unregulated way? What forces determine whether it is optimal to allow the delegated agent to determine the size of the loan? When is it optimal to set the loan size at a low enough level so that all borrowers essentially receive aid, which is what eventually happened with the PPP loans, and when is it optimal to for lenders to distribute larger loans?

The price of delegated discretion is that the lenders' preferences may be poorly aligned with social welfare. The price of regulation or government provision is the business deaths that are caused by delay.

We consider the optimization problem of a benevolent social planner that has a total fund of T dollars to allocate across businesses. We assume that these funds are given as loans, but the problem is unchanged if the money is just a gift. However, note that although the model is unchanged, the parameters governing the public and private benefits of the funding, and their covariances, may vary with the type of funding, so the implications of delayed control versus immediate delegation may vary between a program administered as a grant versus a loan. We will abstract away from many issues that are central to public lending programs, such as ensuring that private lenders have skin-in-the-game and thinking about repayment probabilities.

Our focus is the tradeoff between speed and targeting. The planner will have the option of either immediately having the banking sector allocate funds or delaying long enough to establish more control over the process. This control can come either from direct public delivery of the funds or by crafting terms and incentives that shift the choices of the banking sector. It should be noted that this tradeoff could be ameliorated if the planner had the ability to directly deliver the funds themselves in a rapid and controlled way. In practice, this was likely not possible during this crisis, given the structure of the SBA, but the responsibility could have been given to alternative institutions. Our approach takes these institutions as fixed and characterizes the tradeoffs given these institutional capacity limitations.

We take a reduced form approach to the benefits of the program and assume that if firm i receives x dollars in lending, from either a bank or a public authority, then this will generate $v(x, \alpha_i)$ dollars of public benefit. This benefit can include extra employment, loan repayment, reduced bankruptcy probabilities, and anything good that might flow from public largesse. The term α_i represents the firm-specific benefit of receiving funding, where $v_x(x,\alpha) > 0$, $v_{x\alpha}(x,\alpha) > 0$ and $v_{xx}(x,\alpha) < 0$. We will also specifically assume that $v(x,\alpha) = e^{\alpha}x^{\gamma}, \gamma < 1$, although many of the model's qualitative conclusions are true with a more general functional form.

If α_i were observable, and the social planner directly controlled lending, then it would allocate the T funds to maximize: $\int_{\alpha} v(x,\alpha)f(\alpha)d\alpha$ subject to the constraint $T = \int_{\alpha} xf(\alpha)d\alpha$. We normalize the total population of businesses to equal one, so T would be the amount received per borrower if all loans were equal in size. If second order conditions hold, then social optimal lending would imply that for all values of α that receive loans (and there may be some low α firms that do not), $v_x(x,\alpha) = \lambda$, where λ is a constant, so that the marginal social value of lending is equalized across borrowers

We consider three institutional choices: (1) immediate bank lending, (2) delayed public lending and (3) regulated bank lending, where the regulation fixes the maximum loan size amount for every firm. We will assume that delay is costly because some of the firms have died before the delayed payments can be made. We assume that a random fraction of the firms, denoted $1 - \delta$, disappear because of delay and, consequently, delay eliminates the benefit of lending if the firm dies. There are no other costs of delay in our model other than the loss of potential borrowers.

Immediate Delegation vs. Delayed Control

Our first comparison is between the immediate delegation to banks and delayed control by the planner. Our assumption is that the planner can create a bureaucracy that targets the money to preferred borrowers, albeit imperfectly, if she waits, or she can hand the money over to a bank and let it lend money to their preferred borrowers. We assume a single lending entity allocates T across the entire economy, but the results would be equivalent if we assume there were N banks, each of which had access T/N funds to allocation to a measure 1/N of firms that were randomly selected from the distribution of all firms.

If the bank distributes the funds immediately, it will allocate money to maximize $v(x, \phi\alpha + \xi) = e^{\phi\alpha+\xi}x^{\gamma}$ instead of $v(x, \alpha)$, where $v(x, z) = e^{z}x^{\gamma}$. The variables α and ξ are normally distributed, with mean zero independent random variables and variances σ_{α}^{2} and σ_{ξ}^{2}, respectively. If the government slows down the process, and designs a more targeted allocation mechanism, which may be a hybrid public-private model, then the funds will be allocated to maximize $v(x, \theta\alpha + \zeta) = e^{\theta\alpha+\zeta}x^{\gamma}$, where ζ is a third independent mean zero normal random variable with variance σ_{ζ}^{2}. We will assume that $1 \geq \theta > \phi$ and $\sigma_{\zeta}^{2} \leq \sigma_{\xi}^{2}$.

Delayed targeting must (weakly) increase the correlation of the decision-making with true social value, because the planner always has the option of still using the bank after the delay occurs. We assume that the variance relationship is strict, so that there is some benefit of delay, even if it is tiny. We do not assume that a pure public provision is necessarily better targeted than a bank provision. Politics may significantly distort any public allocation of loans. We do assume that delay allows the creation of some system, public or private or a hybrid, that may provide weakly better targeting than rapidly moving cash out the door.

Proposition 1 follows (all proofs are in Appendix 1):

Proposition 1: There exists a firm survival rate, denoted δ^{*} between 0 and 1, for which public welfare with immediate bank lending is equal to the public welfare with targeted but delayed lending. Targeting provides higher welfare than immediate lending if and only if $\delta > \delta^{*}$. The value of δ^{*} is falling with γ, θ, σ_{ξ}^{2} and σ_{α}^{2} , and rising with ϕ and σ_{ζ}^{2}.

The proposition provides the basic intuition behind the speedy action taken by the CARES Act and the Paycheck Protection Program. There is a survival rate that determines whether delayed targeting is optimal. When the firm dissolution rate is sufficiently large, then immediate non-targeted lending dominates delayed targeting. Abundant evidence suggests that the firm closing rate during this period was extraordinarily high (Bartik et al., 2020a).

This cutoff survival rate depends on the four parameters associated with targeted and non-targeted lending. When the banks' preferences are more closely aligned with social welfare (ϕ is high and σ_{ξ}^{2} is low) then the cutoff survival rate is higher, and immediate lending yields higher welfare for a larger range of survival. When the delayed targeting brings decision-making more closely aligned with social welfare (θ is high and σ_{ζ}^{2} is low), then the cutoff survival rate falls and targeting is optimal even when the odds of survival are lower. Consequently, it was possible to support immediate lending either because of good faith that the banks would take actions that were in the public welfare or because of skepticism towards greater regulation of lending or publicly provided loans.

The survival threshold is also falling with σ_α^2 and γ. The comparative static on σ_α^2 reflects the assumption that $\theta > \phi$ and that delay increases the weight on social welfare in the lending decision. When the heterogeneity in the social welfare of lending to different entities is large, i.e. σ_α^2 is larger, then it is more valuable to delay to improve targeting based on social welfare.

A higher value of γ means that the diminishing returns involved in lending to any one borrower become weaker. Consequently, there may be almost as many benefits to lending to a smaller number of surviving firms as there are lending to a larger number of initial firms. Weaker diminishing returns also means that targeting can lead to larger gains by giving particularly generous loans to high social value borrowers. We now turn to the regulation of lending.

Regulation of Delegated Lending

Previously, we assumed that regulation took time and enabled better targeting of loans. Here we focus on a particularly simple form of regulation that should take no time at all: fixing the loan size. In the previous section, loans were quite flexible and all borrowers received some financing. Here we compare flexibility with a fixed loan size that is small enough so that everyone can borrow.

We first compare fixing the loan size at T with allowing bank flexibility. We then compare whether it is optimal to set the loan size at T, so that all businesses receive the same size loan, or whether the fixed loan size should be larger so that banks can allocate more financing to the firms that they favor, and loan distribution is not universal. Proposition 2 compares bank lending with fixed and flexible quantities:

Proposition 2: When banks allocate loans, fixing the loan size at T generates higher social welfare than allowing bank flexibility if and only if $\frac{1}{2} > \frac{\phi\sigma_\alpha^2}{\sigma_\xi^2+\phi^2\sigma_\alpha^2}$ or $\frac{\sigma_\xi^2}{\sigma_\alpha^2} > 2\phi - \phi^2$.

The condition in Proposition 2 is intuitive. The term $\phi\sigma_\alpha^2$ is the covariance between the social welfare term (α) and the bank's targeting rule ($\phi\alpha + \xi$) while $\sigma_\xi^2 + \phi^2\sigma_\alpha^2$ is the variance of the bank's targeting rule. Consequently, the term $\frac{\phi\sigma_\alpha^2}{\sigma_\xi^2+\phi^2\sigma_\alpha^2}$ is the regression coefficient that would be estimated if social welfare of lending was regressed on the bank's rule. If that slope is more than one-half, so that on average banks get it right, then social welfare benefits by giving the banks discretion. If that slope is smaller than one-half, then higher social surplus is generated by tying the banks hands.

That regression coefficient is larger when σ_α^2 is larger and σ_ξ^2 is smaller, which just means that the ratio of good signal to noise is larger in the bank's lending objectives. If we rewrite the expression as $\frac{\sigma_\xi^2}{\sigma_\alpha^2} > 2\phi - \phi^2$ then it is obvious that higher values of ϕ make fixed loan sizes less appealing.

So far, we have either allowed total flexibility or a low fixed loan size, but neither of those assumptions fits perfectly with the implementation of the PPP in April 2020. Loan sizes were too high to allow all business to borrow, at least at first, but there was a cap to loan size. We now compare loans that are fixed in size at T, with loans that are fixed in size at T'>T. This proposition formally treats the recommendation of Hanson et al. (2020) that more smaller loans may be more advantageous than fewer larger loans. We now assume that $\beta = \phi\alpha + \vartheta\xi$, where $\vartheta = \sqrt{(\sigma_\beta^2 - \phi^2\sigma_\alpha^2)/\sigma_\xi^2}$. This assumption allows us to vary the correlation between bank preferences and social preference (ϕ), without varying the variance of β.

Proposition 3: (i) If banks allocate loans of fixed size T', then if $\phi \leq 0$, then it is never optimal to set T'>T.

(ii) If ϕ >0, then the optimal value of T' is greater than T.

(iii) If a loan size value T' yields the same social welfare as a loan size of T for a given value of γ, denoted $\hat{\gamma}$, then for all values of $\gamma > \hat{\gamma}$, a loan size of T'>T will yield higher welfare than a loan size of T.

(iv) If a loan size value T' yields the same social welfare as a loan size for of T for a given value of ϕ, denoted $\hat{\phi}$, and if $\sigma_\xi^2 = K - \phi^2\sigma_\alpha^2$ for some constant K, then for all values of $\phi > \hat{\phi}$, a loan size of T'>T will yield higher welfare than a loan size of T.

Proposition 3 makes four claims about fixed loan amounts. If $\phi \leq 0$, then loans should be allocated equally across all firms. This case corresponds to zero or negative correlation between the desires of the lenders and the social desirability of targeting a particular buyer. If $\phi > 0$, then some targeting is optimal. The case for targeting is stronger when γ is higher and the social returns to lending are less concave. The case for targeting is also stronger when ϕ is higher, as long as the total variance of bank preferences is held constant. The implication is that better alignment of bank preferences and social preferences should lead to higher lending limits.

IV. Data Description

The survey was conducted by Alignable <www.alignable.com>, the largest network of small businesses across North America, with nearly 5 million members who are either owners or senior managers of small businesses. Alignable regularly sends out polls via emails to network members, and responses to other surveys have been used by researchers to assess the effects of the pandemic on the financial health of small businesses, remote work, and business reopening decisions (Bartik et al. 2020a, Bartik et al. 2020b, Balla-Elliott et al. 2020). The primary survey wave underpinning our analysis of PPP was distributed April 25, 2020, nine days after the final approvals for the first tranche of funding but prior to the second tranche of funds being approved for loans by the SBA. Ninety percent of the survey responses were received prior to April 27, 2020, the first day of the second tranche of the PPP program.

The survey contained information about the business owner's application status for PPP funding, including how much funding had been received to date and the reason for denial or not applying. Following these questions were a series of questions about the owner's relationship with their primary bank and the status of the business, including cash on hand, employment, and beliefs about remaining operation over the following 8 months. The survey also included a series of retrospective questions, including employment, typical monthly payroll, fixed expenditures and typical loan balance with their bank prior to the pandemic.

The Alignable surveys contain a unique identifier allowing us to link individuals to their business profile and other survey waves, which included additional information about prior employment, industry, location, and demographics. We include the survey instrument in the Appendix.

Summary Statistics

Table 1 provides summary statistics about the responses received. We restrict the sample to observations for which our main variables of interest---expected survival probability, whether the firm applied for PPP, impact of COVID on the firm, and information on the firm's banking relationship---are not missing. This leaves us with 6,137 observation - 56% of businesses observed were open at the time of the survey, and 44% were closed. A significant share of respondents forecast upcoming headwinds, as the average reported probability of surviving to December 2020 was 73%.

65% of respondents attempted to apply for PPP funding in the first tranche, and among those that attempted application, 25% were approved. The remaining (51%) were either waiting for approval or had been denied (24%). Our definition of denial includes both rejected applications from the SBA and the inability to apply, which picks up rationing applications. The inability to submit an application accounts for about two-thirds of the 24% who were denied.

At the time of the survey, the average firm had 5.7 employees, down from an average of 9 employees in January, 2020. Firms reported $24,700 in average monthly payroll expenses and $15,100 in fixed monthly expenditures. These averages are somewhat skewed by the few larger firms in our sample. Median current employment, payroll, and fixed expenses are 2 employees, $5,000, and $5,000 respectively. Firms reported having cash on hand to cover about 5.3 weeks worth of expenses.

Approximately one third of the sample reported having primary banking relationship with one of the top 4 largest banks. Twelve percent used banks 5-10, while 10% used a credit union. 40% of firms report having an existing loan with their bank, which includes credit card loans. 23% of firms report having a relationship with a loan officer at their bank.

V. Which Businesses Received a PPP Loan?

We now turn to the factors that determine whether a business applied for and received a PPP loan in our Alignable sample. We will argue that pre-existing banking relationships serve as a plausible source of exogenous variation in the probability of receiving a PPP loan. Consequently, we will document differences in approval rates based on the firms' prior banking experience. First, however, we will establish some basic facts about the correlates between firm characteristics and both application and approval rates. We begin by looking at the application and loan measures captured by different measures of distress, but we emphasize that higher distress may not signify a higher value borrower. We then turn to firm size, age, and industry. We also examine correlates of application rates and outcomes with lender characteristics. Remarkably, application rates are nearly identical among top 4 banks, banks 5-10, and banks 11-20, yet outcomes vary dramatically for these banks' customers. We have checked for differences among female, veteran, and minority owned business and find little difference in either application or approval rates, which is shown in Figure A1 in the appendix.

Applications, Approvals and Distress

The stated goal of the PPP loans was to keep workers paid and employed, which presumably implies that the social benefit of lending to a particular firm (the model's e^{α}), reflects the marginal pay and employment generated per dollar of lending. But are those marginal effects highest for firms that are the weakest or are those firms lost causes, in which case funds would be better spent for firms that are somewhat less distressed?

Figure 2 shows the patterns of application and approval by the impact of COVID-19 on the firm. Firms fall into three categories. Low Impact firms said that COVID-19 is "not impacting my business." Medium Impact firms said that "It's starting to impact by business," and High Impact firms said that "it's really impacting my business."

The application rates rise monotonically with the severity of the crisis to the firm. Over 60 percent of firms who suffered high impact from COVID-19 applied for PPP loans. Fewer than one-fifth of the firms with the least severe harm applied for the loans. We cannot determine if this higher application rate reflects greater demand, or the belief that the most severely impacted firms are more likely to be approved for a PPP loan. Yet if firms have that belief, they are mistaken. The most severely impacted firms are most likely to apply, but they are also the most likely to be denied a PPP loan conditional on application. There are four reasons for denials. First, as discussed above, some banks initially only processed applications from existing customers. Second, some firms did not qualify under the initial program parameters put in place by the SBA. Third, some banks misunderstood the rules put in place by SBA and denied firms that should have qualified. Fourth, firms were unable to submit an application for other reasons. All of these reasons are categorized as denials, although some may have allowed future applications for the second tranche of funds. The denial rate rises from 12% in the lowest severity category to 25% in the highest severity category. The approval rate is roughly the same between the least severe and the median severity category, but lower for the most severely impacted firms.

The gap between approval and denial reflects the large share of firms whose loan applications were pending at the end of the time period. These firms did not receive loans in the first round of the PPP program, and so if the government had been more cash constrained they would have been excluded. In this case, public funding was so generous that we suspect that a large fraction of those firms did eventually receive PPP loans, but our focus here is on expectations for firms that had the knowledge that their loans were approved.

The lower approval rate for higher severity firms could reflect the lender's private incentives to allocate cash to a firm that is more likely to be a valuable client in the future. Alternatively, the higher application rate for high severity borrowers could mean that many of the high severity borrowers had other problems and perhaps were unlikely to survive in any case. While we certainly cannot rule out the possibility that the lenders are behaving in a socially optimal way, it is hard to understand how firms in the lowest severity category can even truthfully certify that "the uncertainty of current economic conditions makes necessary the loan request to support the ongoing operations of the eligible recipient." That certification is a legal requirement for receiving a PPP loan.

Our second measure of firm distress is the amount of cash that the firms have on hand, measured relatively to their usual weekly expenses. In Bartik et al. (2020a), we found that a measure of cash on hand was strongly correlated with firms' expectations of survival probability. Additionally, firms with abundant cash on hand will presumably find it more difficult to truthfully certify that the loan is "necessary" in order to support the firm's "ongoing operations."

Most small firms have relatively little cash on hand, and Figure 3 shows that there is little correlation between the level of cash on hand and the probability of applying for a loan, as long as the firm has two months or less of cash on hand. The application rate does drop from over sixty percent to close to forty percent among those firms that have three months or more cash on hand. Once again, however, we see that pattern where loans were most likely to go to firms that have been impacted the least severely. The approval rate for firms with three of more months of cash on hand is 38 percent. The approval rate for firms with two weeks or less of cash on hand is less than 20 percent. Again, this may be socially optimal because the firms with little cash may fold with or without a loan. However, the higher approval rate for more liquid firms could also reflect the banks private incentives.

Firm Size, Age and Industry

We now turn to differences in applications and approval rates across firm size, age, and industry. Figure 4 shows the patterns of application and approval by the number of employees. Just under one half of firms with zero or one employees applied, which is much lower than other firms. This likely reflects ambiguity around the rules for sole proprietors' eligibility, which came in a SBA announcement on April 10. It is also possible that this limited interest reflects the fact that such firms have much lower (or no) payroll expenses, but it may also reflect a lower return for paying the fixed costs of an application. The application rate then rises to over eighty percent among firms with over six employees.

By contrast, approval rates monotonically increase with firm size. Denial rates and pending rates decrease with firm size. These patterns might reflect the greater capacity of large firms to apply for a loan quickly and with the appropriate documentation. Alternatively, lenders might have been favoring larger firms, because larger loans generate higher fees[13] and because satisfying a larger customer is presumably more valuable than satisfying a smaller customer.

Figure 5 measures firm size, using the firm's monthly fixed expense before the onset of COVID-19. In this case, the application rate is distinctly lower for both the largest and for the smallest firms, in terms of fixed expenditure.[14]

The approval rate appears to be generally increasing with the firm's monthly expenses, which may represent either firm capacity to file swiftly or the lender's interest in taking care of this borrower. The pending and denial rates show less of a clear pattern. The firms with the lowest and the largest expenses have the highest denial rates, perhaps because the larger firms are also asking for larger loans. The pending rate shows little clear pattern, except that the largest firms have a particularly low pending rate.

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[13] Banks received fees equal to five percent of the loan for loans up to $350,000, three percent for loans between $350,000 and $2 million, and one percent for loans above $2 million: https://home.treasury.gov/system/files/136/PPP%20Lender%20Information%20Fact%20Sheet.pdf

[14] Fewer than one-half of the firms with monthly expenses over $500,000 in our sample applied for PPP loans. It is possible that these firms had alternate sources of funding, and that the generally modest size of PPP loans made them unappealing. It is also possible that the few firms that have expenses of that size in the relatively small Alignable survey are non-representative of overall firms in this category.

Figure 6 shows the patterns by business age. Older firms are more likely to apply and more likely to be approved. This pattern could easily mean that the older firms have learned to live with banks, or that their documentation is in better shape. A less benign view is that older firms have a more established relationship with the lender.

Figure 7 shows overall patterns by industry. Application rates were particularly high in accommodation and retail, two sectors that were particularly hammered by COVID-19 and the associated lockdown. Construction also saw high application rates.

Lenders and Approval Rates

We now turn to the nature of the relationship between the lender and the borrower and to the size of the lender. We primarily differentiate between the big four banks, banks ranked five to ten, other large banks (ranked eleven to twenty) and smaller banks.[15] Appendix Table A1 provides the number of borrowers, average loan sizes, and total lending for these four categories. Most lending is done by smaller banks in our sample, but of course, the larger banks handle more loans per bank. Among the respondents, the small banks and credit unions received around 2,000 applications. The big four got about 1,300 application, and banks 5-20 received about one-half of that number.

The gap in applications is much smaller than the gap in total dollar amount that was processed by the lenders in the three categories. The small lenders approved about ten times the value of loans than did any another category of lender. The gap roughly reflects that small banks taken together received twice as many applications, were twice as likely to approve applications, and approved loans at twice the rate of the big banks.

Figure 8 shows the application and approval rates by bank size. For the application rate, we divide the share of firms in our sample who applied to a lender in that category by the sum of that number and the share of firms in our sample who said that their primary lender was in that category but did not apply. The approval, rejection, and pending numbers are all reported as a fraction of the firms that applied to a bank in that category.

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[15] The top 4 banks are J.P. Morgan Chase, Citigroup, Bank of America, and Wells Fargo. Banks 5-10 are U.S. Bank, PNC, Capital One, TD Bank, Truist, and Bank of New York Mellon (which does not appear in our sample). Banks 11-20 are HSBC, Fifth Third, Ally Bank, Citizens Bank, KeyBank, BMO Harris, State Street, Goldman Sachs, Schwab, Morgan Stanley (the last four of which do not appear in our sample).

The application rates are roughly equal across size of lender, although the rate falls slightly among firms that banked regularly with smaller banks. We cannot distinguish if the lower application rate reflects the accessibility of the bank or the characteristics of the borrower. More strikingly, the approval rate is sharply higher for loan applications to banks ranked 11+, with respect to size. Thirty-three percent of applications to non-ranked banks were approved, while only twelve percent of applications to the big four were approved. That heterogeneity in approval rates will lie at the heart of our instrumental variables strategy in the next section.

The denial rates decline slightly with lender size, but the larger difference lies in the pending rate. Small lenders just seem to have been able to handle their loan applications far more expeditiously than the large lenders. One explanation for this difference, which is consistent with reporting around the PPP program, is that the large lenders where simply swamped by the vast number of applications. The smaller banks had to deal with fewer applications per bank and found it easier to scale up their operations.

Appendix Figures A2 - A4 show the approval rates by lender size, based on different types of connections with the bank. Figure A2 shows that approval rates were only slightly higher for firms that had a business account with the bank. Figure A3 shows that borrowers that have an existing loan were significantly more likely to have their loans approved, especially among smaller banks. The probability of being approved was approximately forty percent for firms with existing loans at smaller banks, as opposed to twelve percent among firms without loans at larger banks. Figure A4 show approval rates based on whether the firm already knows a bank loan officer. There is a strong correlation between knowing a loan officer and being approved, especially at smaller banks. This correlation suggests that importance of informal connections between borrowers and lenders, especially during a period when lending is rushed.

One interpretation of these results is that they reflect only the value of personal connections, which help spread knowledge. Another interpretation is that banks guided loans to their indebted clients, who could then use the PPP funds either to remain solvent or possibly even to repay the bank itself. Banks should have a larger incentive to ensure the solvency of firms that owe them larger sums of money, so Figure 9 looks at approval rates by the size of existing loans. All borrowers in this figure have preexisting loans, so presumably all of them have some connection with the bank.

The approval rates are much higher for borrowers with larger existing debt among the smallest lenders. The gap is smaller, but still quite noticeable with the Big Four. Mid-sized banks show the least connection between approval rates and size of existing loan. The magnitudes are striking. The approval rate among firms that already owe more than $500,000 to a small bank was almost 70 percent. By contrast, the approval rate among firm that owe less than $50,000 to a small bank is less than 40 percent.

Perhaps banks disproportionately approved the loans from high debt firms because those firms were particularly likely to go bankrupt without PPP support. To test this possibility, Figure 10 shows approvals rates based on both the size of existing loan and the level of cash on hand. Low levels of cash on hand should suggest more vulnerability, and so if banks are targeting loans to the vulnerable, then low cash on hand should predict a higher approval rate.

The figure shows the opposite. Firms with more cash on hand were more likely to be approved, just as firms with larger debt were more likely to be approved. A firm with less than two weeks of cash on hand and an existing loan under $50,000 experienced a 20 percent change of being approved for a PPP loan. A firm with one to two months of cash on hand and an existing loan or $300,000 had an almost sixty percent change of being approved. These estimates suggest that if a firm with expenses of $200,000 borrowed 1.5 months of expenses before COVID-19 hit, that firm would almost triple their probability of receiving a PPP loan. Consistent with the idea that banks may have steered PPP to firms at high risk of bankruptcy, approval rates are much higher for low-cash firms with large existing debts than other low-cash firms. Appendix Figure A5 shows that impact of have a large loan and low cash is largest among small lenders, but also quite visible for the Big Four.

Table 2 shows these results in a multivariate regression format. The table shows three linear probability models. In the first column, we regress a binary variable that takes a value of one if the firm applies for PPP on firm and lender characteristics. In the second column, we take only those firms that have applied for a loan and regress a binary variable that takes on a value of one if the loan was approved on firm and lender characteristics. In the third column, we again take only firms that applied and use a binary variable that takes on a value of one if the loan was denied as our dependent variable. The coefficients in the second and third regressions will not add to one, because many firms' applications were still pending at the end of our sample period.

The application rates seem primarily to be a function of firm need. The firms that indicated that they were significantly impacted by COVID-19 were 23.8 percentage points more likely to apply for a loan. Firms with significant cash on hand were 12 percent less likely to apply for a loan, holding payroll constant. Firms with a large payroll were 21 percent more likely to apply for a loan, which presumably reflects both the need to meet a large payroll and the ability to cover the fixed costs of applying for a loan.

In the lower half of the table we show the coefficients on lender characteristics and on the relationship between the lender and the bank. The size of the bank doesn't significantly impact application rate, but firms that bank with credit unions are 5.1 percent less likely to apply for a loan. The relationship between lender and borrower does matter. Firms that knew a loan officer were 9.5 percentage points more likely to apply for a loan. Firms that had an existing loan were 4.5 percent more likely to send in an application.

The factors that determine approval are often diametrically opposite to the factors that determine application. Firms that said that COVID-19 impacted them more were 3.3 percent less likely to receive a loan. Firms that had high level of cash were 15.2 percent more likely to receive a loan. A large payroll positively predicts both loan application and loan acceptance. Firms with a large payroll were 13.1 percent more likely to receive a loan.

Bank attributes are far stronger predictors of loan approval than loan application. Firms that have relationship with top four banks are 22.3 percentage points less likely to be approved for a PPP loan. This correlation lies behind our instrumental variables estimates of the impact of PPP loans. A relationship with a bank in the top ten that is outside the top four reduces the probability of loan approval by 14.6 percent. Credit unions also have a strong negative correlation with approval.

The strength of ties to the bank also appear to be important for approval. A preexisting loan with the bank is associated with a 4.4 percentage point increase in the probability of approval. Firms with a preexisting relationship with a bank loan officer were six percentage points more likely to have their loans approved.

The last column shows the coefficients where the dependent variable is being denied the loan. In some cases, the coefficients in this column are exactly the opposite of the coefficients in column (2). For example, the coefficients on high COVID-19 impact, high payroll, being with a credit union and having an existing loan are all within .02 of the comparable coefficient in the second column times minus one. Consequently, this variable shifts firms from denial to approval but has a small impact on the third category: loan pending.

Abundant cash increases approval more than it decreases denial, meaning that firms with more cash, and presumably less need to an immediate infusion of money, were actually less likely to have been left waiting for an answer on their application. Large banks were much more likely to have left applications pending than smaller banks, so the coefficient on denial is much smaller in magnitude than the coefficient on approval. This suggests that the large banks were not being pickier, but they were just unable to handle the large number of loan applications.

The existing loan coefficient for denial is almost exactly equal to minus one times the existing loan coefficient for acceptance, but knowing a loan officer is much more correlated with acceptance than with denial. This suggests that knowing a loan officer helps generate loans because the officer ensures that your application rises to the top of the pile, rather than by converting a denial into an acceptance. We now turn to our estimated impact of PPP loans on firm survival and employment growth.

VI. The Impact of PPP Loans on Expected Firm Survival and Employment

We now turn to the impact of PPP loans of firm's expected survival and employment. We examine both the ordinary least squares coefficient on receiving a PPP among those firms that apply for a PPP loan, and the coefficient where we use the size of their pre-COVID-19 bank as an instrument for receiving a loan. We have two different outcome variables: (1) employment in the April 25 survey and (2) the expected probably of being open during December 2020. The first variable reflects actual employment, rather than expectations, but it may not capture the full impact of a PPP loan, if those loans work primarily by enabling the firm to survive through the summer. Those firms that received a PPP loan should face the incentive to keep their workforce, in order to be eligible for full loan forgiveness. Many of them may not have yet received the funding and so illiquidity may have led them to furlough workers. The expectations variable does capture a longer term outcome, but we must trust the firms' ability to project their own likelihood of surviving. The effect of receiving a PPP loan may be muted if the firms that did not receive a loan expect to get a loan during the next round of PPP lending.

Table 3, Panel A, shows our ordinary least squares results assessing the impact of receiving a PPP loan on the firm's expected probability of remaining open in December 2020. The first column shows that those firms receiving a loan thought that they were fourteen percentage points more likely to remain open in December. The second column includes control for industry and state fixed effect and the coefficient changes little, from .144 to .145. While it is unclear if this result reflects a true treatment effect of the PPP loan, or whether PPP loans have flown to sturdier firms (as suggested by the positive correlation between approval and cash on hand), the estimated coefficients are both large and estimated with reasonable high levels of precision. A further possibility is that the loans have a real treatment effect on the optimism of the firm, but that this will not translate into a higher survival probability.

The third regression controls for whether the business is currently open (business status). The coefficient on receiving a PPP loan drops to .127. Finally, the fourth column includes the amount of cash on hand, which reduces the estimated coefficient to .094, implying that a loan increases the perceived probability of being open in December 2020 by nine percentage points. The coefficient drops when we control for firms with more cash on hand, because firms with cash where more likely to receive loans, and cash on hand is a strong predictor of firms' expectations about their ability to survive.

The final two columns report validation exercise for these measures. Column 5 restricts the sample to include only the firms where we have the phone follow up in late July. Column 6 then changes the dependent variable to an indicator that the phone follow-up returned an affirmative answer to the question of whether the business was operational. For this sample, the expected probability of being operational in December was 73%, whereas 64% of firms answered that they were operational in the follow up phone calls.[16] The coefficients in these specifications are quite similar, with a 9.1 percentage point increase in survival expectations due to PPP in the survey and a 13.7 percentage point increase in the probability of being open in the follow up study. These results improve our confidence that our findings using self-reported expectations about December contain real signal about firm survival probabilities.

Panel (b) repeat these specifications, but using employment as the outcome. Employment is defined as the level of employment in our April 27 survey round, and we control for the level of employment in January. We have experimented with other specifications and the results are

[16] It is difficult to tell definitively whether businesses are closed, as the follow up was unable to reach most businesses that did not respond with a "yes" to the question. Not answering the business phone line is likely correlated with closure, but some non-response is likely due to measurement error that biases the share of operational businesses downward.

broadly similar. The level of employment specification means that the coefficient can be interpreted as the extra jobs associated with receiving a PPP loan. Naturally, we have no way of quantifying how long each of those jobs will last.

The first column shows a coefficient of 3.86, with a standard error of .49 This coefficient suggests that the average loan was associated with almost four extra jobs. In the second column, we control for industry and state fixed effects. The estimated coefficient declines slightly to 3.76. In the third specification, we control for business status and the coefficient falls to 3.39. When we also control for cash on hand in the fourth column, the coefficient declines to 3.1.

The controls do lead to an attenuation of the coefficient, but it remains highly significant statistically and quite reasonable in terms of economic magnitude. As the average PPP loan in our sample is $185,000, this represents about $60,000 dollars per employee. Any cost-benefit analysis of that price, however, must both address the duration of these jobs and whether these payments to firms represent lost resources or simply a transfer.

The endogeneity of the loan approval leads to our instrumental variable strategies. Our first strategy restricts firms to those whose primary banking relationship is with one of the nation's 20 largest banks. We then use two indicator variables that take on a value of one either if the bank is among the four largest, or if the bank is ranked between five and ten. This strategy leverages the fact that loans were more likely to be approved by smaller banks. We restrict our sample, though to firms with lenders among the top 20 to ensure reasonable comparability among the borrowers. The first stage F-statistic is 18.4 for our base specification using this instrument.
Our second strategy is to restrict the sample to those firms that banked with either community banks or credit unions before the COVID-19 crisis. We then instrument for receiving a loan with being a customer of a credit union. The mean approval rate was 17 percent for Credit Unions and 41 percent for Community Banks. The first stage F-statistic is 6.0 for the core specification with this instrument. These two samples are both somewhat different, as one skews towards the customers of big banks and the other towards the customers of small banks. Consequently, we see the use of both samples as testing whether slightly different identification strategies used on somewhat different samples yield comparable results.

Table 4, Panel A, shows results for expectations about being open in December. Table 4, Panel B, provides our findings for employment. The first four regressions in Panel A and Panel B show results for the large bank sample. The second four regressions in each panel provide results for sample with smaller lenders.

The estimated coefficient is .22 in the first regression, which includes no other controls, and .21 in the fourth regression, where we control for industry, state, cash on hand and business status. The first and fourth regressions yield almost identical coefficients, because controlling for state and industry fixed effects lead the estimated coefficients to rise and controlling for cash on hand leads the estimated coefficients to fall. In the second coefficient, where we control for industry and state, but not the endogenous business attributes, the coefficient rises to .3. In the third regression, where we control for the business being open, the coefficient drops slight to .28. These estimates are larger than the ordinary least squares coefficients. The equivalent of the fourth regression in Table 3 yields a coefficient of .094, which is more than fifty percent below the Table 4 coefficient. The instrumental variables estimates of PPP treatment effects should be higher than the ordinary least squares estimates if loans were flowing to firms that would otherwise have a lower probability of survival. Some evidence supports that view. Firms that have existing loans were more likely to receive a loan. But other evidence is contradictory, firms that reported a larger impact of COVID-19 or less cash on hand were actually less likely to receive a loan. Alternatively, the instrumental variables estimates may be biased upwards, if the identity of a firm's pre-COVID-19 lender is correlated with expected survival probability for other reasons. A third possibility, which we examine further below, is that PPP flowed to firms for which the effect of receiving funds was small.

Regressions (5)-(8) in Table 4, Panel A show results using our second instrumental variables procedure and they are broadly similar. The coefficient in regression (5) is almost exactly the same as the coefficient in regression (1). The coefficients in (6) and (7) are higher than those in regression (5), but lower than the coefficients in (2) and (3). Finally, regression (8) shows a more dramatic drop when we control for cash on hand. The coefficient falls to .14, which is not statistically distinct from zero at conventional significance levels, but it is still larger than the equivalent coefficient in Table 3 and it is not statistically distinct from the coefficients estimated in (5), (6) or (7).

In Panel B, we show our results for employment, following the same structure as Panel A. The coefficients are generally not statistically different from zero, but they are also quite close to the ordinary least squares estimates. For example, the ordinary least squares coefficient with all of our controls is 3.1. The instrumental variable estimates using the Credit Union instrument is 3.31. The parallel estimate in column (4) is 4.99.

The coefficients are uniformly higher with the large bank sample. The coefficients are also quite insensitive to different specifications ranging from 4.99 to 5.63. Given the standard errors, there are reasons to be careful about accepting these coefficients, yet their similarity to our more precisely estimated ordinary least squares coefficients provides us with somewhat more confidence in the employment estimates in Table 3.

Heterogeneous Treatment Effects

While the average impact of receiving a PPP loan on survival and employment is important for evaluating the overall program, the heterogeneity of treatment effects is more important for evaluating the delegated implementation of the program. If all loans had the same social impact, then there is no social welfare loss in allowing lenders to decide who receives what loan, or just allocating the loans randomly for that matter. If the impact on employment or survival was much higher for some borrowers than for others, then the allocation rules that lenders followed become more important.

Table 5 estimates heterogeneous treatment effects of PPP loans on expected survival probability along six different dimensions. Each column considers one form of heterogeneity. Panel A shows IV results for the full sample, using Top 4, Top 5-10, and Credit Union dummies interacted with dummies for above/below median characteristics Z as instruments. Panel B shows results for the big lender sample. Panel C shows results for Credit Unions and Community Banks. These specifications include no other controls except dummies for the baseline characteristics Z. The first column splits the sample based on the impact of COVID-19 to the business. In all cases, the split of variable Z is at the median value of the variable. The top coefficient in Panel A shows that receiving a PPP loan increased the expected probability of survival by 22 percentage points among those firms that were more impacted by COVID-19. The bottom coefficients shows that receiving a PPP loan increased the expected probability of survival by only 12 percentage points among firms that were less impacted by COVID-19. This difference is intuitive. As the PPP loans were meant to reduce the damage done by COVID-19, it is reassuring that the loans had a larger impact on expected survival for those firms that were more impacted by COVID-19.

In Panels B and C, we show the instrumental variables coefficients for the firms that were more and less impacted by COVID-19 impact. The large lender sample shows results that are comparable to the IV results in Panel A. Among the more impacted businesses, receiving a PPP loan improves the probability of survival by over twenty percentage points. There is essentially no impact among firms that were not impacted by COVID-19 in panel B.

The bottom panel, however, finds the opposite pattern. The coefficient on the highly impacted subsample is positive but not distinct from zero. The coefficient on the less impacted subsample is extremely large, but also not distinct from zero. We conclude that the Credit Union/Community Bank sample of banks has too little variation to estimate the heterogeneous treatment effects by COVID-19 impact.

In the second column, we show results based on cash on hand. Again, Panels A and B show similar, intuitive results. The expected survival impact of a PPP loan is estimated by .125 for firms with more cash on hand in the top panel and .073 for the more liquid firms in Panel B. The estimate impact of the loan on the more constrained firms is estimated at .21 in the top panel and .15 in the bottom panel. These differences are understandable, if PPP loans were more valuable for firms that had less cash on hand.

Panel C shows a larger impact of firms with more cash, perhaps because of the different sample of borrowers. Cash on hand appears to reduce the impact of a PPP loan among the large lender sample and overall, but not among the small lender sample. One possible explanation is that in the small bank sample, the firms without cash stand little chance of survival with or without PPP loans, and so the marginal impact of those loans is larger with firms that have cash on hand. Alternatively, the results for this sample could just reflect noise.

The third and fourth regressions interact receiving a PPP loan with the ex ante relationship between the borrower and the bank. In panel A and B, the coefficients are quite similar. Knowing a loan officer does not appear to increase the impact of receiving a loan on expected survival. Having a pre-existing loan does not increase the impact of a PPP loan on expected survival. If true, these results suggest that the tendency of banks to target loans towards firms with pre-existing relationships does not increase the probability that the loan will enable a firm to survive.

In panel C, we find that knowing a bank officer is associated with a lower treatment effect but having a pre-existing loan is associated with a higher treatment effect. These results are not impossible. Bank officers could favor businesses that they like over businesses where the loan would have a larger marginal impact. Firms with pre-existing loans may be closer to closing and may experience a larger treatment effect of a PPP loan. However, given the larger standard errors and the divergence between these coefficients and the coefficients in Panels A and B, we tend to interpret these differences as reflecting primarily noise.

The final two regressions split the sample based on either payroll expenditures or overall fixed expenditures. In all three specification, the impact of a PPP loan of firm survival is larger among firms with larger payroll levels. The difference in coefficients is also statistically significant in Panel A. Among firms with larger payrolls, a PPP loan is associated with a 31 percentage point increase in expected survival in the ordinary least squares specification, a 32 percentage point increase in expected survival in the large lender instrumental variables specification and a 20 percentage point increase in expected survival in the smaller lender specification. All of these coefficients are statistically distinct from zero.

In Panels A and B, the impact of loans on expected survival for low payroll firms is quite close to zero. In Panel C, we estimate that receiving a PPP loan reduces the probability of survival by nine percentage points, but this is not statistically significant. These results do suggest that lending had more impact when firms have more workers to pay.

In the sixth and final column, we show results where we split by fixed expenditures. The estimated impact of the PPP loans was larger for firms with lower levels of fixed expenditures in Panels A and B, possibly because PPP loan forgiveness only applies to payroll expenditures, not fixed expenses. In other words, the program is effectively more generous for low fixed expenditure firms. The impact was larger for firms with high levels of fixed expenditures in Panel C. Standard errors prevent us from concluding much here, but it does seem as if payroll may indicate the marginal return from loans more than fixed expenditures.

Table 6 shows results on employment where we split the sample along the same six variables. In no case is the difference in coefficients significant. In some cases, the instrumental variables estimates are statistically different from zero in one of the subsamples.

Panel A shows only one column where there are treatment effects that seem economically different in magnitude. Once again, the loans appear to have a larger impact for firms with higher levels of payroll. Among high payroll firms, a PPP loan is associated with an extra 5.5 employees. Among low payroll firms, a loan is associated with only an extra 2 employees. While these results seem reasonable and in line with the Table 4 results, the difference is not statistically significant.

In Panel B, the coefficient is also higher for the high payroll sample. The coefficient is again 5 in the high payroll set of firms and effectively zero in the low payroll set of firms. Panel B estimates also suggests that the loans are more effective in firms which have been impacted more by COVID-19 and firms with less cash on hand. These results are also in line with the results found in Table 4.

In Panel C, we find no differences that are economically or statistically meaningful. Our instrument just does not appear to be powerful enough to estimate heterogeneous treatment effects in this sample. We now turn to whether the characteristics that predict greater impact of PPP loans, also increase the probability of receiving a PPP loan.

Was the Allocation of Loans Efficient?

Tables 7 and 8 ask whether the variables that predict loan effectiveness also predict loan applications and loan approvals. Table 7 looks at loan applications. Table 8 examines loan approvals. The columns mirror the columns in Table 5 and 6, so column one splits the businesses based on COVID-19 impact, column two splits on cash and so forth. We show coefficients from OLS regressions based on having above or below the median value of the variable, just as we do in Tables 5 and 6. The regressions are run without an intercept so that the coefficient can be interpreted as the share of firms in each group that applied, or conditional upon applying, the share of firms that were approved. Consequently, the two coefficients can be multiplied to determine the share of firms in each group that actually received a loan in the first round.

All regressions are ordinary least squares, but we still have three panels in each table, corresponding to the different samples in the two instrumental variables specifications. Panel B includes only those firms that banked with a large bank prior to the crisis. Panel C includes only those firms that banked either with a Credit Union or a Community Bank.

The first column in Table 7, Panel A, shows that 71.2 percent of firms that claimed a high COVID-19 impact applied for PPP loans, and only 44 percent of firms that claimed a low COVID-19 impact applied for those loans in the overall sample. Panels B and C show that those probabilities are quite similar to the probabilities in the different subsamples. These application rates seem in line with the estimates in Panels A and B of Table 4 and Panel B of Table 5 showing that PPP loans were more effective for firms suffered more impact from COVID-19.

However, the first column of Table 8 shows that firms that faced a larger impact from COVID-19 were actually less likely to have their loans approved, which also appeared in Table 2 regression 2. For the overall sample, 23 percent of firms that experienced a high impact where approved as opposed to 34 percent of firms that experienced a low impact. Multiplying the probabilities in Tables 6 and 7 together suggests that 16.6 percent of firms facing high COVID-19 impact received loans while 15 percent of firms facing low COVID-19 impact received PPP loans. High COVID-19 impact induced more applications but lower approval rates and on net the two forces cancelled each other out, so that the system did little to target founds towards firms that were more impacted by COVID-19.

If we examine the two subsets, we find that in the large bank sample 11.1 percent of high COVID impact firms received PPP loans and 9.8 percent of low COVID impact firms received loans. In the small lender sample, 22.8 percent of high impact firms received loans and 18.7 percent of low impact firms received loans. The small lenders were more effective at processing the loans and the did a slightly better job of targeting the funds towards firms that had experienced more of an impact from COVID-19.

Again in Table 5, Panels A and B, and Table 6 panel B, we found that the loans were more effective for firms that had less cash on hand. Were those firms more likely to receive loans? In Table 7, Panel A, we find that 58 percent of firms with more cash apply for PPP loans and 73 percent of firms with less cash apply for PPP loans in the overall sample. The applications figures are roughly comparable for the other samples as well.

Table 8, Panels A, B and C, show that the approval rates are much high for firms that have more cash on hand. Multiplying both probabilities together, in the overall sample, the chance that a high cash firm received a loan is 20.4 percent. The chance that a low cash firm received a loan is 11.7 percent. In Panels B and C, the overall chance that a low cash firm received a loan is much higher than the chance that a high cash firm received a loan. This system certainly did not seem to target funds well towards the most desperate borrowers, many of whom appeared to have particularly high returns to borrowing.

The relationship variables did not have a strong correlation with the impact of lending, but they did increase the probability of receiving a loan. For example, knowing a loan officer seems to have increase the probability that a firms receives a loan from 12.8 percent to 26.4 percent in the overall sample. Having an outstanding loan to the lender increases the probability of receiving a PPP loan from 17.4 percent to 28.4 percent among the small lenders. Connections with the bank did seem to play a role in allocating loans, although those connection-based do not seem to have reduced the efficacy of PPP loans on average.

The interaction with personnel costs was the strongest effect in Tables 5 and Table 6. In Table 7 and Table 8, we do indeed find that firms with more personnel costs were more likely to apply and to receive loans. High personnel cost firms in the overall sample received a loan with a 30 percent probability. Low personnel cost firms received a loan with an 8.4 percent probability. In this case, high personnel cost firms were both more likely to apply for a loan and more likely to receive a loan.

Overall, the results on efficacy were mixed. Firms that were impacted by COVID-19 more were not significantly more likely to receive a loan, even though some of our measures indicate that the returns to loans were higher for that group. Firms with connections to the banks were more likely to receive loans, even though the loans do not seem more effective for that group. However, loans flowed more steadily to firms with higher payroll costs and the loans were more effective for those firms. Along this important latter dimension at least, the allocation mechanism appears to have been well matched to social returns.

Table 9 takes an omnibus look at application and approval based on an index of individual treatment effects from Tables 5 and 6. We regress application and approval on $Z\hat{\beta},$ estimated in these prior tables, which allows us to assess demand for PPP based on our estimates of heterogeneous benefits as well as actual deployment of funds. Although there is a disconnect between demand for PPP and approval rates based on the benefit to the firm, in no case is the approval rates coefficient negative. Based on a benchmark of purely random allocation of loans (where we would expect a zero coefficient), the banks' targeting rules appear to do slightly better than random. It is an open question whether different rules would have brought the approval rates closer to overall loan demand for firms with high treatment effects, but doing so would have likely delayed the process. In fact, our source of identifying variation for these effects likely comes from banks own delays in processing applications, which yielded lower approval rates.

VII. Conclusion

Using survey data on business owners collected by the Alignable network, we link receipt of a Paycheck Protection Program loan with expectations of firm survival and reported employment levels. We find large survival effects when instrumenting PPP receipt with the firm's banking relationship, while effects on employment are positive and imprecisely estimated. Despite the very generous provisions of PPP that make the program attractive for most firms, the applicants in our sample exhibit self-selection in applying based on their need. Among the small firms that constitute the majority of small business in the United States and in our sample, those more affected by COVID-19, with less cash-on-hand, and with higher payroll costs were more likely than others to apply for PPP. Application patterns may differ for larger SMEs with over 250 employees, but these firms make up a small fraction of our sample.

The targeting effectiveness of loan approval was more mixed. On some dimensions, we find that the program allocated funds well, with firms estimated to have higher treatment effects being more likely to be approved. On the other hand, firms with stronger connections to banks were more likely to have their applications approved, while firms more negatively affected by COVID and with less cash-on-hand were less likely to be approved, suggesting that lending to bank customers in better financial positions may have been prioritized, possibly crowding out less connected firms that would have had greater benefits from the loans.

Relative to an emerging literature studying this unprecedented program, we believe ours is the first paper to lever individual firm level data linked to program application and approval through the banking relationship. This unique dataset allows us to study the costs and benefits of allocating public aid for firms through private financial intermediaries. We are also able to uniquely focus on a segment of smaller firms, where identification may be challenging using other strategies.

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APPENDIX 1: Proofs of Propositions

Proof of Proposition 1: If the banks hand out cash $e^{\phi\alpha+\xi}x^{\gamma-1}$ is constant over borrowers or $x = \left(e^{\beta}/k_B\right)^{\frac{1}{1-\gamma}}$, where k_B solves the adding up constraint of $T = \int_{\beta} \left(e^{\beta}/k_B\right)^{\frac{1}{1-\gamma}} g(\beta)d\alpha$, or $T = (k_B)^{\frac{-1}{1-\gamma}} e^{\frac{\sigma_\beta^2}{2(1-\gamma)^2}}$, where $\beta = \phi\alpha + \xi$ and σ_β^2 is the variance of β. This implies that under bank landing, $x = Te^{\frac{\beta}{1-\gamma} - \frac{\sigma_\beta^2}{2(1-\gamma)^2}}$. Condition upon α, welfare based on bank discretion is $\int_{\xi} e^{\alpha}\left(Te^{\frac{\phi\alpha+\xi}{1-\gamma} - \frac{\sigma_\beta^2}{2(1-\gamma)^2}}\right)^{\gamma} h(\xi)d\xi = e^{\frac{(1-\gamma+\phi\gamma)\alpha}{1-\gamma}} T^{\gamma} e^{-\frac{\gamma(\phi^2\sigma_\alpha^2)}{2(1-\gamma)^2}} e^{-\frac{\gamma\sigma_\xi^2}{2(1-\gamma)}}$. Integrating over α then yields total social welfare of $T^{\gamma}e^{\frac{(1-\gamma(1-\phi)^2)\sigma_\alpha^2 - \gamma\sigma_\xi^2}{2(1-\gamma)}}$

Under public lending, $e^{\theta\alpha+\zeta}x^{\gamma-1}$ is constant over borrowers or $x = \frac{T}{\delta}e^{\frac{q}{1-\gamma} - \frac{\sigma_q^2}{2(1-\gamma)^2}}$, where $q = \theta\alpha + \zeta$ and σ_q^2 is the variance of β. Welfare equals $\int_{\alpha} \delta e^{\alpha}\left(\frac{T}{\delta}e^{\frac{q}{1-\gamma} - \frac{\sigma_q^2}{2(1-\gamma)^2}},\right)^{\gamma} m(q)dq = \delta^{1-\gamma}T^{\gamma}e^{\frac{(1-\gamma(1-\theta)^2)\sigma_\alpha^2 - \gamma\sigma_\zeta^2}{2(1-\gamma)}}$.

Welfare is higher with delay if and only if $\delta^{1-\gamma}T^{\gamma}e^{\frac{(1-\gamma(1-\theta)^2)\sigma_\alpha^2 - \gamma\sigma_\zeta^2}{2(1-\gamma)}} > T^{\gamma}e^{\frac{(1-\gamma(1-\phi)^2)\sigma_\alpha^2 - \gamma\sigma_\xi^2}{2(1-\gamma)}}$ or $\delta > e^{\gamma\frac{[(1-\theta)^2-(1-\phi)^2]\sigma_\alpha^2 + \sigma_\zeta^2 - \sigma_\xi^2}{2(1-\gamma)^2}}$. This condition clear does not hold when $\delta = 0$ and must hold when $\delta = 1$ as we have assumed that $[(1-\phi)^2 - (1-\theta)^2]\sigma_\alpha^2 + \sigma_\xi^2 - \sigma_\zeta^2 > 0$. As the left hand side is monotonic and continuous in δ, there must exist a value of a firm survival rate, denoted δ^* between zero and 1, for which public welfare with immediate bank lending is equal to the public welfare with delayed targeting. Targeting provides higher welfare that immediate lending if and only if $\delta > \delta^*$, where $\delta^* = e^{-\gamma\frac{[(1-\phi)^2-(1-\theta)^2]\sigma_\alpha^2 - \sigma_\zeta^2 + \sigma_\xi^2}{2(1-\gamma)^2}}$. Differentiation then yields that δ^* is falling with $\gamma, \theta, \sigma_\xi^2$ and σ_α^2 , and rising with ϕ and σ_ζ^2.

Proof of Proposition 2: If loan sizes are fixed at a level T so that everyone receives a loan, then total public welfare is $T^{\gamma}e^{\frac{\sigma_\alpha^2}{2}}$ since the average value of e^{α} is $e^{\frac{\sigma_\alpha^2}{2}}$. Total public welfare from flexibly sized loans is $T^{\gamma}e^{\frac{(1-\gamma(1-\phi)^2)\sigma_\alpha^2-\gamma\sigma_\xi^2}{2(1-\gamma)}}$, so fixed loans yields higher welfare if and only if $\sigma_\alpha^2(1-\gamma) > (1-\gamma(1-\phi)^2)\sigma_\alpha^2 - \gamma\sigma_\xi^2$ or $\frac{1}{2} > \frac{\phi\sigma_\alpha^2}{\sigma_\xi^2+\phi^2\sigma_\alpha^2}$ or $\frac{\sigma_\xi^2}{\sigma_\alpha^2} > 2\phi - \phi^2$.

Proof of Proposition 3: If loan sizes are fixed at T'>T, then there will be a minimum value of $\beta = \phi\alpha + \vartheta\xi$ (where $\vartheta = \sqrt{(\sigma_\beta^2 - \phi^2\sigma_\alpha^2)/\sigma_\xi^2}$) that is serviced by the banks, and we denote that minimum $\hat{\beta}$, which solves $\frac{T}{T'} = 1 - G(\hat{\beta})$ or $T' = \frac{T}{\int_{\beta>\hat{\beta}} e^{\frac{-\beta^2}{2\sigma_\beta^2}} d\beta}$.

As T' determines $\hat{\beta}$ exactly, we will think of the social planner as choosing $\hat{\beta}$ rather than T' for mathematical convenience. Social welfare from lending equals $\left(\int_{\beta>\hat{\beta}} e^{\frac{-\beta^2}{2\sigma_\beta^2}} d\beta\right)^{-\gamma} T^{\gamma} \int_{\beta>\hat{\beta}} E(e^{\alpha}|\beta)\, g(\beta) d\beta$where $E(e^{\alpha}|\beta) = \frac{\int_\alpha e^{\alpha} h\left(\frac{\beta-\phi\alpha}{\vartheta}\right) f(\alpha) d\alpha}{\int_\alpha h\left(\frac{\beta-\phi\alpha}{\vartheta}\right) f(\alpha) d\alpha} =$

$$\frac{\int_\alpha e^{\alpha} e^{-\frac{(\beta-\phi\alpha)^2}{2\vartheta^2\sigma_\xi^2}} e^{-\frac{\alpha^2}{2\sigma_\alpha^2}} d\alpha}{\int_\alpha e^{-\frac{(\beta-\phi\alpha)^2}{2\vartheta^2\sigma_\xi^2}} e^{-\frac{\alpha^2}{2\sigma_\alpha^2}} d\alpha} = e^{\frac{2\beta\phi\sigma_\alpha^2 + \vartheta^2\sigma_\xi^2\sigma_\alpha^2}{2\sigma_\beta^2}}$$

Hence the overall objective function is $e^{\frac{\sigma_\alpha^2}{2}} T^{\gamma}$ times

$$\left(\int_{\beta>\hat{\beta}} e^{\frac{-\beta^2}{2\sigma_\beta^2}} d\beta\right)^{-\gamma} \int_{\beta>\hat{\beta}} e^{\frac{-(\beta-\phi\sigma_\alpha^2)^2}{2\sigma_\beta^2}} d\beta = V(\hat{\beta}; Z)$$, were Z is a vector of exogenous variables.

Welfare when everyone gets T equals $e^{\frac{\sigma_\alpha^2}{2}} T^{\gamma}$.

Welfare when selected individuals receive T'>T, equals $T^{\gamma} e^{\frac{\sigma_\alpha^2}{2}}$ times

$$\left(\int_{\beta>\hat{\beta}} e^{\frac{-\beta^2}{2\sigma_\beta^2}} d\beta\right)^{-\gamma} \int_{\beta>\hat{\beta}} e^{\frac{-(\beta-\phi\sigma_\alpha^2)^2}{2\sigma_\beta^2}} d\beta = V(\hat{\beta}; Z)$$, were Z is a vector of exogenous variables.

We also know that $\int_{\beta>\hat{\beta}} e^{\frac{-\beta^2}{2\sigma_\beta^2}} d\beta = \frac{T}{T'}$, and that (using a simple change of variable so that $x = \beta - \phi\sigma_\alpha^2$, we have $\int_{\beta>\hat{\beta}} e^{\frac{-(\beta-\phi\sigma_\alpha^2)^2}{2\sigma_\beta^2}} d\beta = \int_{x>\hat{\beta}-\phi\sigma_\alpha^2} e^{\frac{-x^2}{2\sigma_\beta^2}} dx$.

Hence $\left(\int_{\beta>\hat{\beta}} e^{\frac{-\beta^2}{2\sigma_\beta^2}} d\beta\right)^{-\gamma} \int_{\beta>\hat{\beta}} e^{\frac{-(\beta-\phi\sigma_\alpha^2)^2}{2\sigma_\beta^2}} d\beta = \left(\int_{\beta>\hat{\beta}} e^{\frac{-\beta^2}{2\sigma_\beta^2}} d\beta\right)^{-\gamma} \int_{\beta>\hat{\beta}-\phi\sigma_\alpha^2} e^{\frac{-\beta^2}{2\sigma_\beta^2}} d\beta$

If $\phi = 0$, then this equals $\left(\frac{T}{T\prime}\right)^{1-\gamma}$, which will be less than 1 whenever T'>T and $1 > \gamma$.

If $\phi < 0$, then $\int_{x>\hat{\beta}-\phi\sigma_\alpha^2} e^{\frac{-x^2}{2\sigma_\beta^2}} dx < \int_{\beta>\hat{\beta}} e^{\frac{-\beta^2}{2\sigma_\beta^2}} d\beta = \frac{T}{T\prime}$ and so $V(\hat{\beta}; Z) < \left(\frac{T}{T\prime}\right)^{1-\gamma} \leq 1$, whenever T'>T and $1 > \gamma$. Consequently, it is never welfare enhancing to let T'>T if $\phi \leq 0$.

The derivative of $V(\hat{\beta}; Z)$ with respect to $\hat{\beta}$ yields:

$\gamma e^{\frac{-\hat{\beta}^2}{2\sigma_\beta^2}} \left(\int_{\beta>\hat{\beta}} e^{\frac{-\beta^2}{2\sigma_\beta^2}} d\beta\right)^{-\gamma-1} \int_{\beta>\hat{\beta}-\phi\sigma_\alpha^2} e^{\frac{-\beta^2}{2\sigma_\beta^2}} d\beta - \left(\int_{\beta>\hat{\beta}} e^{\frac{-\beta^2}{2\sigma_\beta^2}} d\beta\right)^{-\gamma} e^{\frac{-(\hat{\beta}-\phi\sigma_\alpha^2)^2}{2\sigma_\beta^2}}$, which is positive if and only if $\gamma > \frac{e^{\frac{2\phi\sigma_\alpha^2\hat{\beta}-\phi^2\sigma_\alpha^4}{2\sigma_\beta^2}} \int_{\beta>\hat{\beta}} e^{\frac{-\beta^2}{2\sigma_\beta^2}} d\beta}{\int_{\beta>\hat{\beta}-\phi\sigma_\alpha^2} e^{\frac{-\beta^2}{2\sigma_\beta^2}} d\beta}$. If $\phi > 0$, then as $\hat{\beta}$ goes to negative infinity (which corresponds to T=T'), the right hand side of the equation goes to zero, and consequently, increasing T' above T is optimal.

The derivative of $V(\hat{\beta}; Z)$ with respect to γ is $-\left(\int_{\beta>\hat{\beta}} e^{\frac{-\beta^2}{2\sigma_\beta^2}} d\beta\right)^{-\gamma} \int_{\beta>\hat{\beta}} e^{\frac{-(\beta-\phi\sigma_\alpha^2)^2}{2\sigma_\beta^2}} d\beta \, ln\left(\int_{\beta>\hat{\beta}} e^{\frac{-\beta^2}{2\sigma_\beta^2}} d\beta\right) > 0$, and so that if some value of T'>T yields the same welfare as T for any value of γ, then for all values of $\gamma' > \gamma$, an allocation of T' will yield higher welfare than T.

If the variance of β is independent of ϕ, then the derivative of $V(\hat{\beta}; Z)$ with respect to ϕ (holding σ_β^2 constant) is positive, and given by $\sigma_\alpha^2 e^{\frac{-\hat{\beta}^2+2\phi\sigma_\alpha^2\hat{\beta}-\phi^2\sigma_\alpha^4}{2\left(\phi^2\sigma_\alpha^2+\sigma_\xi^2\right)}} \left(\int_{\beta>\hat{\beta}} e^{\frac{-\beta^2}{2\sigma_\beta^2}} d\beta\right)^{-\gamma} > 0$. Consequently, if some value of T'>T yields the same welfare as T for any value of ϕ,then for all values of $\phi' > \phi$ (holding σ_β^2 constant), T' will yield higher values of $V(\hat{\beta}; Z)$.

Appendix 2: Survey Instrument

What impact are you currently experiencing from the Coronavirus Outbreak?

- O It's not impacting my business
- O It's starting to impact my business
- O It's really impacting my business
- O The impact is on the decline
- O The impact is over

Have you applied for any loans or assistance under the government's Payroll Protection Plan?

- O Approved, and I have received the funds
- O Approved, but I have not yet received the funds
- O Application is pending
- O Application was denied
- O I tried to apply but was unable to submit an application
- O I did not apply

When did you first apply for a loan?

Did your bank give you any of the following reasons for the denied loan application? (Please select all that apply)

- ☐ Insufficient documentation
- ☐ Did not meet federal qualification criteria
- ☐ Did not apply in time to receive funds
- ☐ Not a priority customer
- ☐ I received a different reason (not listed here)
- ☐ I did not receive a reason

How much assistance did you receive?

- O Less than $10k
- O Between $10-25k
- O Between $25-50k
- O Between $50-75k
- O Between $75-100k
- O Between $100-150k
- O Between $150-300k
- O Between $300-500k
- O Between $500k-$1 million
- O $1 million - $2 million
- O $2 million - $3 million
- O $3 million - $4 million
- O $4 million - $5 million
- O $5 million - $6 million
- O $6 million - $7 million
- O $7 million - $8 million
- O $8 million - $9 million
- O $9 million - $10 million

O $10 million - $20 million

O More than $20 million

Which of the following reasons describes why you did not apply? Please select all that apply.

- ☐ I can remain operational without extra cash
- ☐ I've already taken out a business loan and don't want to take on any more loans
- ☐ I don't want to deal with the hassle of applying
- ☐ I don't think I would receive the money in time for it to help my business
- ☐ I don't feel confident I can maintain my payroll for the loan to be forgiven
- ☐ I don't trust that the government will forgive my loan even if I maintain my payroll
- ☐ I don't trust that my bank will forgive my loan even if I maintain my payroll
- ☐ I don't believe I qualify for this loan (credit history, size of business, etc.)
- ☐ I don't trust that the COVID-19 disruptions will be over soon enough for my business to recover so I can maintain my payroll or pay back the loan
- ☐ I'm confused about the terms of the loan
- ☐ I would prefer other assistance that does not risk going into debt and being unable to pay it back
- ☐ I've applied for a loan before and was denied
- ☐ Closure is inevitable, even with the cash
- ☐ Other, please specify: ____

How many of the following types of workers, **including yourself,** will your business employ in the first week of May?

_______ Full-Time employees

_______ Part-Time / Temporary employees

What is the likelihood of your business remaining operational by Dec. 31, 2020? Please provide your best guess.

- O Extremely Likely
- O Very Likely
- O Somewhat Likely
- O Somewhat Unlikely
- O Extremely Unlikely

What is the likelihood of your business remaining operational by Dec. 31, 2020? Please provide your best guess.

- O 0% Extremely Unlikely
- O 10%
- O 20%
- O 30%
- O 40%
- O 50%
- O 60%
- O 70%
- O 80%
- O 90%
- O 100% Extremely Likely

Is your business open?

- O Yes, it is currently open.
- O No, it is temporarily closed due to COVID-19, but I intend to reopen.
- O No, it is temporarily closed for other reasons, but I intend to reopen.
- O No, it is permanently closed due to COVID-19.
- O No, it is permanently closed for other reasons.

How many of the following types of workers, **including yourself,** did this business employ on January 31st before COVID-19 disruptions?

_______ Full-Time employees

_______ Part-Time / Temporary employees

How much was your typical monthly payroll before COVID-19 disruptions?

- O Less than $10k
- O Between $10-25k
- O Between $25-50k
- O Between $50-75k
- O Between $75-100k
- O Between $100-150k
- O Between $150-300k
- O Between $300-500k
- O Between $500k-$1 million
- O $1 million - $2 million
- O $2 million - $3 million
- O $3 million - $4 million
- O $4 million - $5 million
- O $5 million - $6 million
- O $6 million - $7 million
- O $7 million - $8 million
- O $8 million - $9 million
- O $9 million - $10 million

O More than $10 million

Some of your business expenses, like rent and interest payments, don't change even when you're not open.   What was the total of these fixed expenses before COVID-19 disruptions, each month?

- Less than $10k
- Between $10-25k
- Between $25-50k
- Between $50-75k
- Between $75-100k
- Between $100-150k
- Between $150-300k
- Between $300-500k
- Between $500k-$1 million
- $1 million - $2 million
- $2 million - $3 million
- $3 million - $4 million
- $4 million - $5 million
- $5 million - $6 million
- $6 million - $7 million
- $7 million - $8 million
- $8 million - $9 million
- $9 million - $10 million

O More than $10 million

Consider the cash you have on hand today. How long will the cash you have today last under the current COVID-19 disruptions?

O Already gone

O Less than 2 weeks

O 2 weeks to 1 months

O 1 to 2 months

O 3 months or more

Have you taken the following actions? (select all that apply)

- [ ] Reduced Pay Rates (per person)
- [ ] Reduced Rent Payments
- [ ] Reduced Loan Payments
- [ ] Reduced Mortgage Payments
- [ ] None of the above

Who is your primary bank? (start typing, then select a name)

____

How likely are you to recommend your bank to someone else?

- O 0
- O 1
- O 2
- O 3
- O 4
- O 5
- O 6
- O 7
- O 8
- O 9
- O 10

What was the nature of your relationship with that bank? (Please select all that apply)

- [ ] I had a loan or credit card from the bank
- [ ] I had a business bank account
- [ ] I used the bank for services other than loans or a bank account
- [ ] I had a relationship with a banker or loan officer
- [ ] None of the above

How large was your typical loan balance with the bank in total ($) before COVID-19 disruptions?

- Less than $10k
- Between $10-25k
- Between $25-50k
- Between $50-75k
- Between $75-100k
- Between $100-150k
- Between $150-300k
- Between $300-500k
- Between $500k-$1 million
- $1 million - $2 million
- $2 million - $3 million
- $3 million - $4 million
- $4 million - $5 million
- $5 million - $6 million
- $6 million - $7 million
- $7 million - $8 million
- $8 million - $9 million
- $9 million - $10 million

O More than $10 million

What is your main industry?

- O Agriculture, Forestry, Fishing and Hunting
- O Mining, Quarrying, and Oil and Gas Extraction
- O Utilities
- O Construction
- O Manufacturing
- O Wholesale Trade
- O Retail Trade
- O Transportation and Warehousing
- O Information
- O Finance and Insurance
- O Real Estate and Rental and Leasing
- O Professional, Scientific, and Technical Services
- O Management of Companies and Enterprises
- O Administrative Support or Waste Remediation Services
- O Educational Services
- O Health Care and Social Assistance
- O Arts, Entertainment, and Recreation
- O Accommodation and Food Services

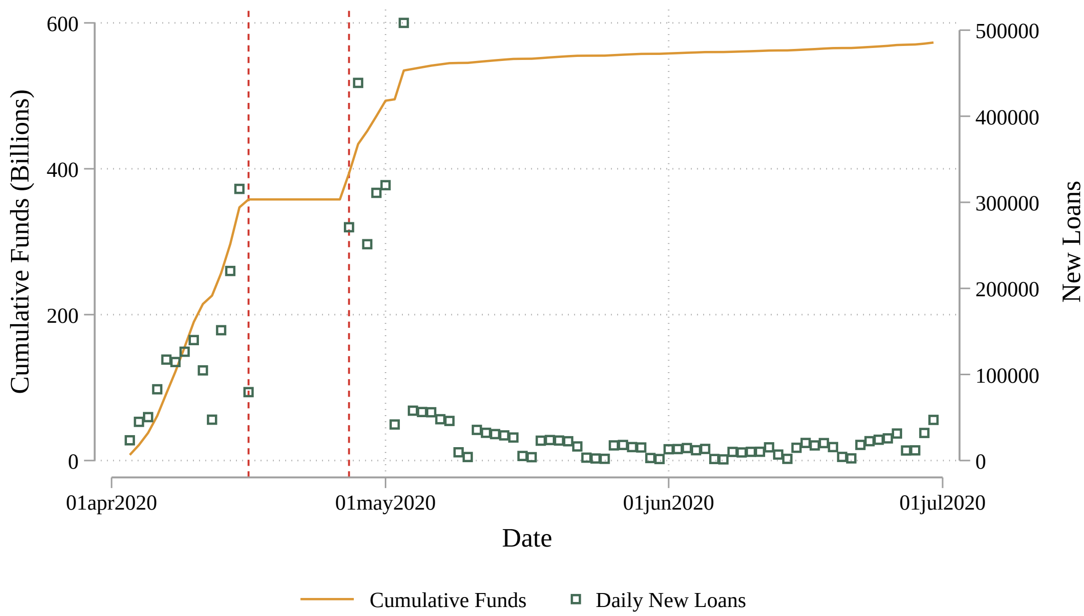
O Other Services (except Public Administration)

O Public Administration

Once more for the books! What is the likelihood of your business remaining operational by Dec. 31, 2020? Please provide your best guess.

- O Extremely Likely
- O Very Likely
- O Somewhat Likely
- O Somewhat Unlikely
- O Extremely Unlikely

Figure 1. PPP program daily new loan approvals and cumulative funds deployed over time, based on data provided by the SBA.



Red lines indicate the end of tranche 1 on 4/16/2020 and the beginning of tranche. 2 on 4/27/2020. Cumulative funds are overstated due to using the midpoint of amounts for loans over $150k.

Figure 2. Fraction of respondents applying and application outcomes by impact of Covid on the firm as of April 27, 2020. Low impact firms reported that COVID-19 is "not impacting my business." Medium impact firms said that "It's starting to impact by business," and high impact firms said that "it's really impacting my business." The sample includes 3993 firms that report expectations of surviving until December 2020 and Covid impact.

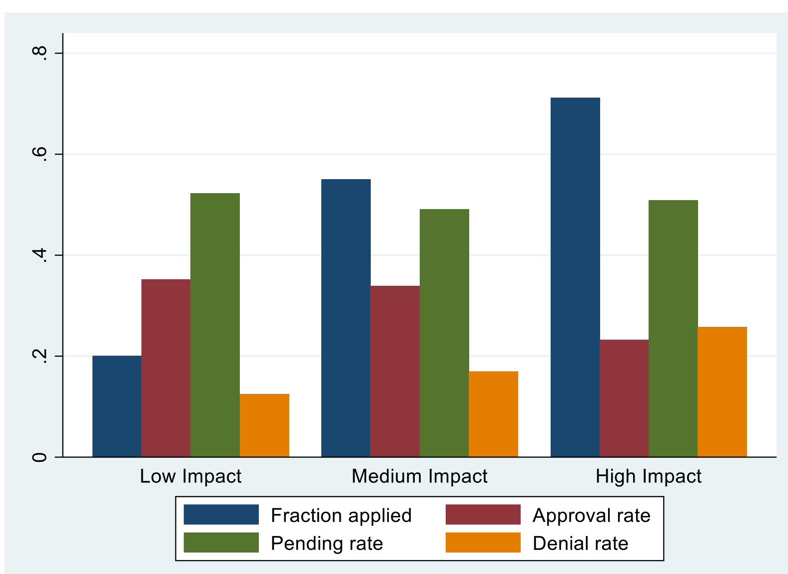


Figure 3. Fraction of respondents applying and application outcomes by amount of cash on hand as of April 27, 2020. Respondents were asked "Consider the cash you have on hand today. How long will the cash you have today last under the current disruptions?" The sample includes 3993 firms that report expectations of surviving until December 2020 and Covid impact.

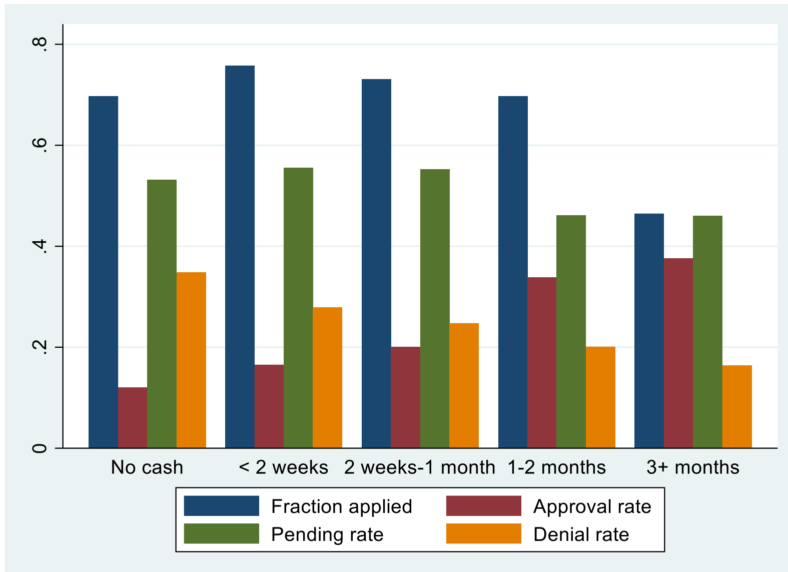


Figure 4. Fraction of respondents applying and application outcomes as of April 27, 2020 by January employment. The sample includes 4571 firms that report employment and Covid impact.

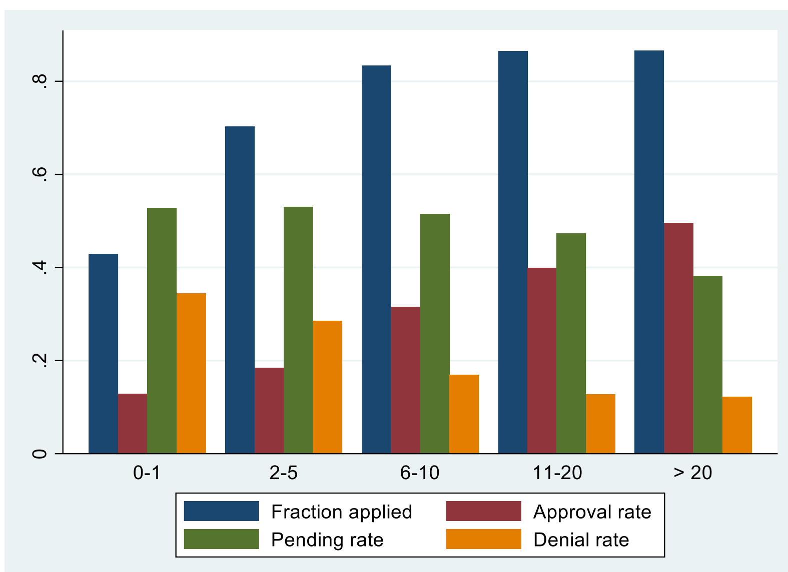


Figure 5. Fraction of respondents applying and application outcomes as of April 27, 2020 by pre-Covid fixed monthly expenses ($000s). Fixed expenses come from the survey question "Some of your business expenses, like rent and interest payments, don't change even when you're not open. What was the total of these fixed expenses before COVID-19 disruptions, each month?" The sample includes 3993 firms that report expectations of surviving until December 2020 and Covid impact.

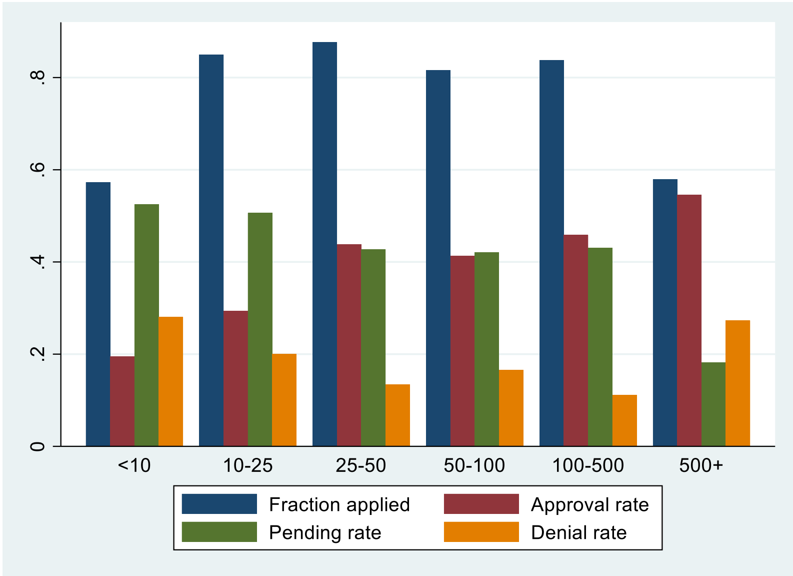


Figure 6. Fraction of respondents applying and application outcomes as of April 27, 2020 by business age. The sample includes 2383 firms that report their age.

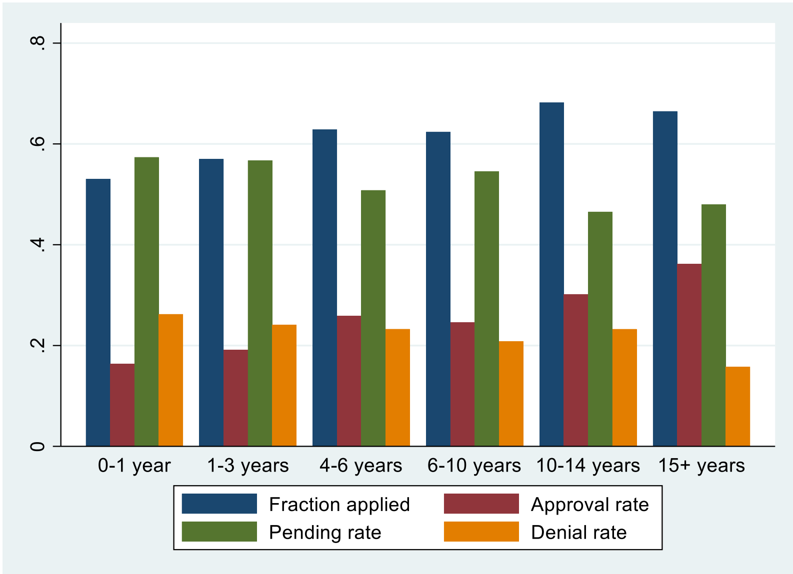


Figure 7. Fraction of respondents applying and application outcomes as of April 27, 2020 by industry. The sample includes 3993 firms that report expectations of surviving until December 2020 and Covid impact.

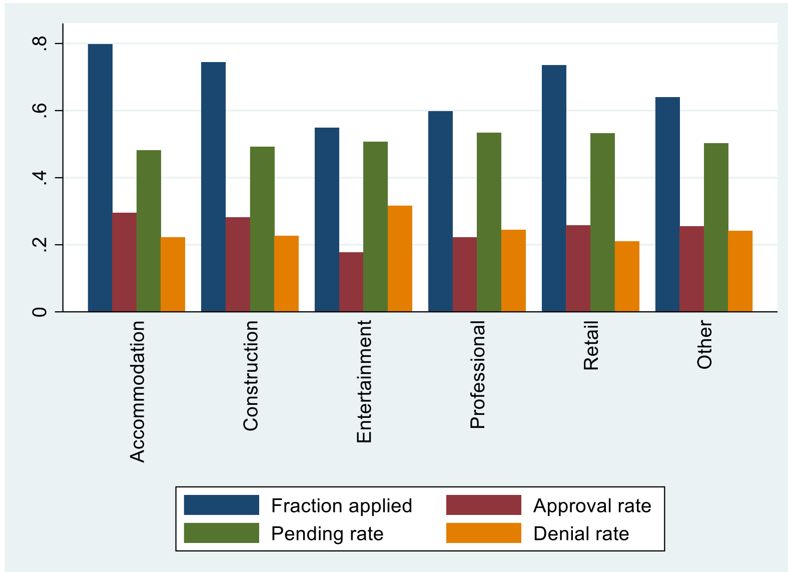


Figure 8. Fraction of respondents applying and application outcomes as of April 27, 2020 by bank size. The sample includes 3993 firms that report expectations of surviving until December 2020 and Covid impact.

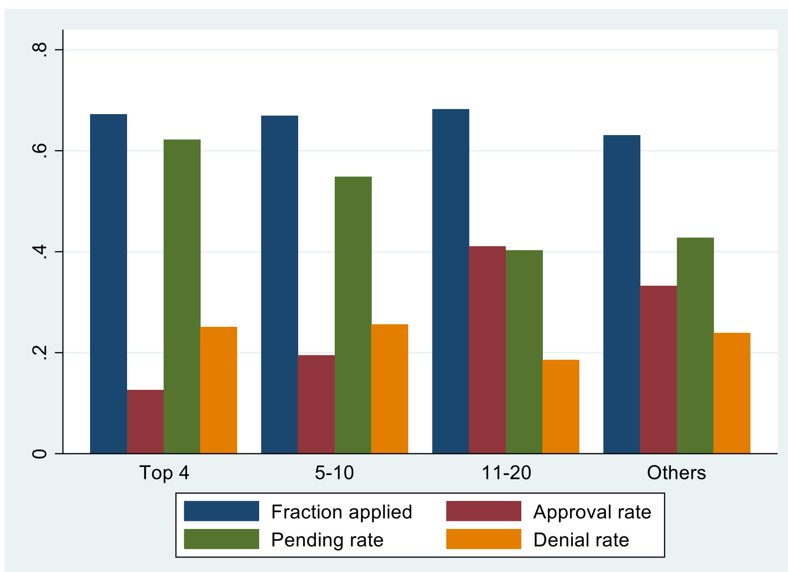


Figure 9. Approval rates by bank size and the size of the firm's existing loan. The sample includes 2559 firms that applied for PPP and report loan amounts.

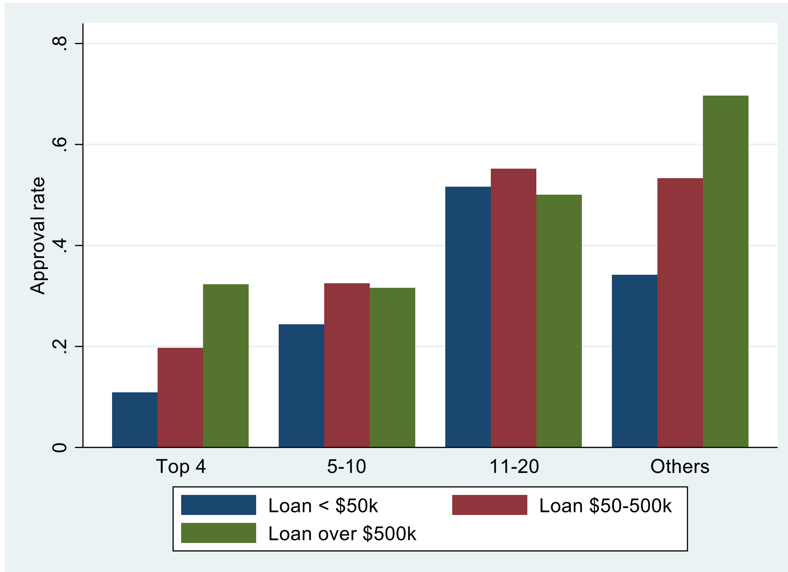


Figure 10. Approval rates by cash on hand as of April 27, 2020 and size of the firm's existing loan. Respondents were asked "Consider the cash you have on hand today. How long will the cash you have today last under the current disruptions?" The sample includes 2559 firms that applied for PPP and report loan amounts.

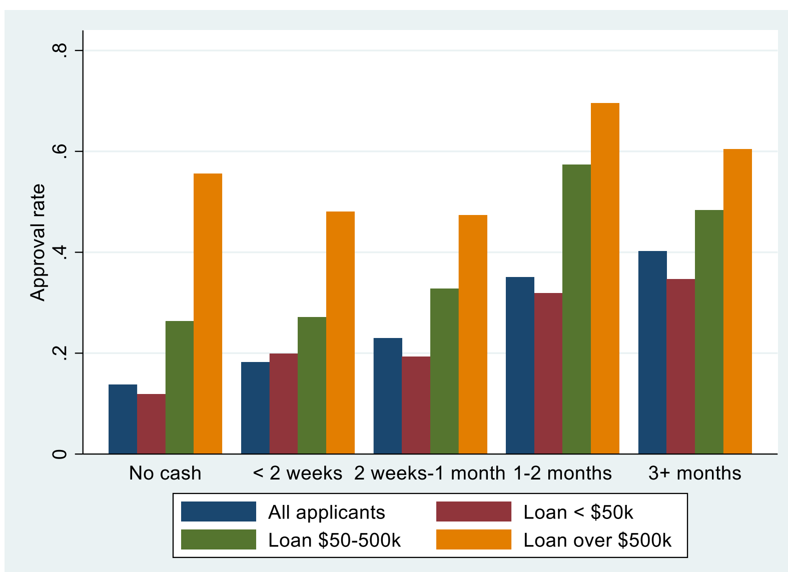


Table 1. Summary Statistics. This table reports summary statistics for our sample. Survival expectations are the probability a firm expects to be open in December 2020. PPP denied/unable is an indicator that the firm was unable to apply for PPP or that the SBA denied the application. Cash is cash on hand, reported in terms of weeks the firm's cash will last if its current impact from Covid-19 persists. This variable is top-coded at 12 weeks. Payroll and fixed expenses are for the typical month before Covid-19 disruptions. Top 4, top 5-10, and credit union are all dummies indicating the type of bank the firm uses. Existing loan indicates the firm had a loan from its bank prior to PPP. Loan officer indicates the firm has a relationship with a loan officer at its bank.

	N	mean	sd	p25	p50	p75
Currently Open	6137	0.56	0.50	0	1	1
Survival Exp	6137	0.73	0.29	0.5	0.8	1
Applied for PPP	6137	0.65	0.48	0	1	1
PPP Approved	3993	0.25	0.43	0	0	0
PPP Pending	3993	0.51	0.50	0	1	1
PPP Denied/Unable	3993	0.24	0.43	0	0	0
4/27 Employees	5994	5.70	21.59	1	2	5
Jan Employees	5994	8.78	41.80	1	3	7
High Covid Impact	6137	0.77	0.42	1	1	1
Cash (weeks)	6137	5.29	4.51	1	6	12
Payroll ($k)	6137	24.67	76.24	5	5	17.5
Fixed Expenses ($k)	6137	15.14	39.91	5	5	17.5
Top 4 Bank	6137	0.32	0.47	0	0	1
Top 5-10 Bank	6137	0.12	0.32	0	0	0
Credit Union	6137	0.10	0.30	0	0	0
Existing Loan	6137	0.40	0.49	0	0	1
Loan Officer	6137	0.23	0.42	0	0	0

Table 2. PPP Applications, Approvals, and Denials. This table relates application, approval, and denial rates for PPP as of April 27, 2020 to firm characteristics. In the second and third columns, the sample is restricted to firms that applied for PPP. Standard errors clustered by bank are reported in parentheses.

	Application Rate	Approval Rate	Denial Rate
High Covid Impact	0.242	-0.033	0.047
	0.018	(0.017)	(0.017)
High Cash	-0.113	0.152	-0.075
	0.012	(0.015)	(0.013)
High Payroll	0.204	0.131	-0.133
	0.010	(0.019)	(0.014)
Top 4 Bank	0.021	-0.223	0.030
	0.017	(0.015)	(0.027)
Top 5-10 Bank	0.019	-0.146	0.034
	0.025	(0.019)	(0.017)
Credit Union	-0.037	-0.123	0.101
	0.017	(0.027)	(0.012)
Existing Loan	0.052	0.044	-0.042
	0.008	(0.012)	(0.011)
Loan Officer	0.086	0.060	-0.020
	0.013	(0.018)	(0.013)
	0.17	0.16	0.06
	6137	4644	4644

Table 3. Expectations, Operational Status, Employment, and PPP Approval: OLS. This table runs OLS regressions relating whether a firm had been approved for the PPP program as of April 27, 2020 to its expectations of survival at the time of the survey, operational status as-of late July, and employment at the time of the survey. The sample is restricted to firms that applied for PPP, including firms that were ultimately denied and firms that tried to apply but were unable to submit an application. Sample sizes are somewhat larger here than in the following tables because we do not condition on the firm reporting the impact of Covid in this table. In Columns 1-5 of Panel A, the dependent variable is the probability a firm expects to be open in December 2020. Firms report the probability of being open in December in 10 percentage point increments. The dependent variable is in raw units. Column 5 of Panel A restricts to the sample in Column 6. Column 6 reports the results of a phone audit of a random sample of these businesses where owners were asked if they were open or operational in late July. Answers are coded as 1 if the owner answers yes and 0 for owners who answer no or if there is no response to two separate phone calls. In Panel B, the dependent variable is employment as of April 27, 2020, and we control for firm employment in January. In both panels, column 2 controls for industry and state, column 3 for whether the business is currently open or closed, and column 4 for its remaining cash on hand. Standard errors reported in parentheses, clustered by bank.

Panel A: Survival Expectations and July Operational Status

	Survival Expectations					Status
	(1)	(2)	(3)	(4)	(5)	(6)
PPP approved	0.144	0.145	0.127	0.094	0.091	0.137
	(0.007)	(0.008)	(0.007)	(0.007)	(0.010)	(0.020)
Adj R2	0.05	0.09	0.14	0.20	0.21	0.097
N	4509	4509	4509	4509	2328	2328
Industry FE	N	Y	Y	Y	Y	Y
State FE	N	Y	Y	Y	Y	Y
Bus Status FE	N	N	Y	Y	Y	Y
Cash FE	N	N	N	Y	Y	Y

Panel B: Employment

	(1)	(2)	(3)	(4)
PPP approved	3.86	3.76	3.39	3.10
	(0.49)	(0.51)	(0.51)	(0.48)
Adj R2	0.45	0.45	0.46	0.46
N	5840	5840	5840	5840
Jan. Emp Control	Y	Y	Y	Y
Industry FE	N	Y	Y	Y
State FE	N	Y	Y	Y
Bus Status FE	N	N	Y	Y
Cash FE	N	N	N	Y

Table 4. Expectations, Employment, and PPP Approval: IV. This table runs IV regressions relating whether a firm had been approved for the PPP program as of April 27, 2020 to its expectations of survival and employment. The sample is restricted to firms that applied for PPP. In Panel A, the dependent variable is the probability a firm expects to be open in December 2020. Firms report the probability of being open in December in 10 percentage point increments. The dependent variable is in raw units. In Panel B, the dependent variable is employment as of April 27, 2020, and we control for employment in January. In both panels, columns 1-4 restrict the sample to firms with banks in the top 20 and instrument for PPP approval with whether the firm's bank is ranked 1-4 or 5-10. The first stage F-statistic is 18.4. Columns 5-8 restrict the sample to firms with community banks and credit unions and instrument for PPP approval with whether the firm's bank is a credit union. Columns 2 and 6 control for the firm's state and industry. Columns 3 and 7 control for whether the business is currently open, its industry, and its state. Columns 4 and 8 control for whether the business is currently open, its remaining cash on hand, its industry, and its state. Standard errors reported in parentheses, clustered by bank in columns 1-4 and by state in columns 5-8.

Panel A: Survival Expectations								
	Top 20 Banks				Community Banks/Credit Unions			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PPP approved	0.216	0.301	0.276	0.205	0.219	0.233	0.221	0.140
	(0.054)	(0.085)	(0.085)	(0.081)	(0.053)	(0.069)	(0.070)	(0.081)
Adj R2	0.01	0.02	0.07	0.16	0.06	0.10	0.14	0.19
N	2214	2214	2214	2214	1090	1090	1090	1090
Industry FE	N	Y	Y	Y	N	Y	Y	Y
State FE	N	Y	Y	Y	N	Y	Y	Y
Bus Status FE	N	N	Y	Y	N	N	Y	Y
Cash FE	N	N	N	Y	N	N	N	Y

Panel B: Employment								
	Top 20 Banks				Community Banks/Credit Unions			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PPP approved	5.61	5.63	5.03	4.99	1.87	3.21	3.17	3.31
	(4.02)	(4.13)	(4.16)	(4.20)	(1.47)	(2.11)	(2.05)	(2.51)
Adj R2	0.47	0.47	0.48	0.48	0.71	0.70	0.71	0.71
N	2830	2830	2830	2830	1395	1395	1395	1395
Jan. Emp. Control	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	N	Y	Y	Y	N	Y	Y	Y
State FE	N	Y	Y	Y	N	Y	Y	Y
Bus Status FE	N	N	Y	Y	N	N	Y	Y
Cash FE	N	N	N	Y	N	N	N	Y

Table 5. Survival Expectations and PPP Approval: Heterogeneous treatment effects. This table relates the probability a firm expects to be open in December 2020 to whether it had been approved for the PPP program as of April 27, 2020 as function of firm characteristics denoted Z. The sample is restricted to firms that applied for PPP. Firms report the probability of being open in December in 10 percentage point increments. The dependent variable is in raw units. Panel B restricts the sample to firms with banks in the top 20 and instruments for PPP approval interacted with Z with whether the firm's bank is ranked 1-4 or 5-10, also interacted with Z. Panel C restricts the sample to firms with community banks and credit unions and instruments for PPP approval interacted with Z with whether the firm's bank is a credit union, also interacted with Z. Panel A combines the sample and uses all instruments. Standard errors reported in parentheses, clustered by bank in Panel B and by state in Panels A and C.

	Panel A: All firms					
Z =	Covid Impact	Cash	Loan	Officer	Payroll	Fixed Exp
PPP approved x	0.223	0.125	0.200	0.233	0.305	0.188
high Z	(0.041)	(0.036)	(0.033)	(0.064)	(0.041)	(0.055)
PPP approved x	0.123	0.212	0.281	0.204	-0.011	0.270
low Z	(0.066)	(0.094)	(0.078)	(0.065)	(0.125)	(0.065)
Adj R2	0.09	0.12	0.02	0.03	0.00	0.02
N	3993	3993	3993	3993	3993	3993

	Panel B: Top 20 Banks					
Z =	Covid Impact	Cash	Loan	Officer	Payroll	Fixed Exp
PPP approved x	0.212	0.073	0.218	0.268	0.315	0.137
high Z	(0.080)	(0.068)	(0.082)	(0.115)	(0.067)	(0.083)
PPP approved x	0.008	0.151	0.255	0.214	0.004	0.267
low Z	(0.132)	(0.155)	(0.125)	(0.097)	(0.106)	(0.101)
Adj R2	0.076	0.114	0.000	0.001	0.000	0.000
N	1958	1958	1958	1958	1958	1958

	Panel C: Community Banks/Credit Unions					
Z =	Covid Impact	Cash	Loan	Officer	Payroll	Fixed Exp
PPP approved x	0.090	0.162	0.268	0.088	0.204	0.299
high Z	(0.073)	(0.080)	(0.100)	(0.163)	(0.071)	(0.105)
PPP approved x	1.238	0.028	0.065	0.163	-0.096	0.049
low Z	(1.592)	(0.174)	(0.200)	(0.095)	(0.215)	(0.172)
Adj R2	0.00	0.11	0.02	0.07	0.00	0.00
N	957	957	957	957	957	957

Table 6. Employment and PPP Approval: Heterogeneous treatment effects. This table relates firm employment to whether it had been approved for the PPP program as of April 27, 2020 as function of firm characteristics denoted Z. The sample is restricted to firms that applied for PPP. We control for January employment in all specifications. Panel B restricts the sample to firms with banks in the top 20 and instruments for PPP approval interacted with Z with whether the firm's bank is ranked 1-4 or 5-10, also interacted with Z. Panel C restricts the sample to firms with community banks and credit unions and instruments for PPP approval interacted with Z with whether the firm's bank is a credit union, also interacted with Z. Panel A combines the sample and uses all instruments. Standard errors reported in parentheses, clustered by bank in Panel B and by state in Panels A and C.

	Panel A: All firms					
Z =	Covid Impact	Cash	Loan	Officer	Payroll	Fixed Exp
PPP approved x	7.31	7.58	9.04	7.76	5.51	6.95
high Z	(2.66)	(2.41)	(1.97)	(2.39)	(2.16)	(3.45)
PPP approved x	7.92	6.84	6.07	7.56	2.07	5.62
low Z	(3.74)	(4.23)	(3.94)	(3.72)	(3.41)	(4.12)
Adj R2	0.45	0.45	0.44	0.44	0.53	0.47
N	4571	4571	4571	4571	4571	4571
Jan. Emp. Control	Y	Y	Y	Y	Y	Y

	Panel B: Top 20 Banks					
Z =	Covid Impact	Cash	Loan	Officer	Payroll	Fixed Exp
PPP approved x	6.79	3.64	3.65	4.74	5.00	8.86
high Z	(3.31)	(4.06)	(3.22)	(6.04)	(2.31)	(4.23)
PPP approved x	1.00	9.46	8.83	5.49	-0.01	3.08
low Z	(5.69)	(6.66)	(5.23)	(3.58)	(4.69)	(4.40)
Adj R2	0.48	0.48	0.48	0.49	0.55	0.50
N	2217	2217	2217	2217	2217	2217
Jan. Emp. Control	Y	Y	Y	Y	Y	Y

	Panel C: Community Banks/Credit Unions					
Z =	Covid Impact	Cash	Loan	Officer	Payroll	Fixed Exp
PPP approved x	-1.05	1.41	-0.37	-0.37	-0.12	5.78
high Z	(1.79)	(1.72)	(2.05)	(3.12)	(1.73)	(3.65)
PPP approved x	13.35	-3.05	0.66	-0.41	-1.08	-4.39
low Z	(17.63)	(4.01)	(2.70)	(2.29)	(5.67)	(3.05)
Adj R2	0.72	0.74	0.74	0.74	0.75	0.73
N	1083	1083	1083	1083	1083	1083
Jan. Emp. Control	Y	Y	Y	Y	Y	Y

Table 7. Heterogeneity in PPP Application Rates. This table reports OLS regressions relating the probability a firm has applied for the PPP program as of April 27, 2020 as a function of firm characteristics denoted Z. The model is run without a constant, so coefficient estimates are means for each group. Panel A examines all firms, Panel B restricts the sample to firms with banks in the top 20, and Panel C restricts the sample to firms with community banks and credit unions. The regressions are run with no constant so the coefficients are the means for high- and low-Z firms. Standard errors reported in parentheses, clustered by bank in Panel B and by state in Panels A and C.

	Panel A: All firms					
Z =	Covid Impact	Cash	Existing Loan	Loan Officer	Payroll	Fixed Exp
High Z	0.712	0.579	0.708	0.776	0.821	0.848
	(0.008)	(0.010)	(0.011)	(0.014)	(0.010)	(0.010)
Low Z	0.440	0.726	0.613	0.613	0.547	0.573
	(0.011)	(0.011)	(0.011)	(0.009)	(0.009)	(0.009)
Adj R2	0.67	0.66	0.65	0.66	0.68	0.67
N	6137	6137	6137	6137	6137	6137

	Panel B: Top 20 Banks					
Z =	Covid Impact	Cash	Existing Loan	Loan Officer	Payroll	Fixed Exp
High Z	0.726	0.591	0.716	0.809	0.831	0.852
	(0.011)	(0.016)	(0.015)	(0.016)	(0.013)	(0.014)
Low Z	0.474	0.750	0.640	0.639	0.572	0.599
	(0.015)	(0.012)	(0.016)	(0.013)	(0.012)	(0.012)
Adj R2	0.69	0.68	0.67	0.68	0.70	0.69
N	2912	2912	2912	2912	2912	2912

	Panel C: Community Banks/Credit Unions					
Z =	Covid Impact	Cash	Existing Loan	Loan Officer	Payroll	Fixed Exp
High Z	0.697	0.571	0.678	0.761	0.818	0.832
	(0.012)	(0.017)	(0.020)	(0.016)	(0.013)	(0.018)
Low Z	0.420	0.706	0.602	0.583	0.533	0.560
	(0.029)	(0.016)	(0.018)	(0.014)	(0.016)	(0.015)
Adj R2	0.65	0.64	0.63	0.64	0.66	0.66
N	1512	1512	1512	1512	1512	1512

Table 8. Heterogeneity in PPP Approval Rates. This table reports OLS regressions relating the probability a firm has been approved for the PPP program as of April 27, 2020 as a function of firm characteristics denoted Z. The model is run without a constant, so coefficient estimates are means for each group. Panel A examines all firms, Panel B restricts the sample to firms with banks in the top 20, and Panel C restricts the sample to firms with community banks and credit unions. The regressions are run with no constant so the coefficients are the means for high- and low-Z firms. Standard errors reported in parentheses, clustered by bank in Panel B and by state in Panels A and C.

	Panel A: All firms					
Z =	Covid Impact	Cash	Existing Loan	Loan Officer	Payroll	Fixed Exp
High Z	0.233	0.353	0.288	0.354	0.352	0.341
	(0.017)	(0.031)	(0.025)	(0.027)	(0.029)	(0.027)
Low Z	0.341	0.162	0.219	0.209	0.155	0.195
	(0.033)	(0.012)	(0.016)	(0.016)	(0.013)	(0.017)
Adj R2	0.25	0.29	0.25	0.27	0.29	0.27
N	3993	3993	3993	3993	3993	3993

	Panel B: Top 20 Banks					
Z =	Covid Impact	Cash	Existing Loan	Loan Officer	Payroll	Fixed Exp
High Z	0.154	0.232	0.180	0.203	0.219	0.218
	(0.013)	(0.033)	(0.026)	(0.029)	(0.027)	(0.021)
Low Z	0.207	0.111	0.148	0.150	0.111	0.130
	(0.028)	(0.010)	(0.012)	(0.015)	(0.014)	(0.016)
Adj R2	0.16	0.18	0.16	0.16	0.18	0.17
N	1958	1958	1958	1958	1958	1958

	Panel C: Community Banks/Credit Unions					
Z =	Covid Impact	Cash	Existing Loan	Loan Officer	Payroll	Fixed Exp
High Z	0.327	0.469	0.419	0.470	0.513	0.475
	(0.027)	(0.038)	(0.034)	(0.039)	(0.041)	(0.042)
Low Z	0.445	0.227	0.289	0.281	0.205	0.274
	(0.041)	(0.021)	(0.024)	(0.022)	(0.020)	(0.022)
Adj R2	0.35	0.39	0.36	0.37	0.41	0.37
N	957	957	957	957	957	957

Table 9. Applications, Approvals, and Estimated PPP Effects. This table relates PPP application and approval rates as of April 27, 2020 to our estimates of PPP's effect on the probability a firm expects to be open in December 2020. The dependent variable in the first three columns of the table is an indicator for whether the firm applied to PPP. The dependent variable in the last three columns in an indicator for whether the firm was approved as of April 27. To form a firm-level estimate of PPP's effect, we take an equal-weighted average of effects implied by Table 4. For example, if a firm is highly impacted by Covid, has high cash, does not have an existing bank loan, does not have a relationship with a loan officer, has low payroll, and has low fixed costs, we average the coefficients on (PPP Approved x high Z) in columns (1) and (2) of Table 4 with the coefficients on (PPP Approved x low Z) in columns (3)-(6) of Table 4. Columns (1) and (4) of the table use estimates for all firms, corresponding to Table 4 Panel A. Columns (2) and (5) use estimates for firms with banks in the top 20 (Table 4 Panel B). Columns (3) and (6) use estimates for firms with community banks and credit unions (Table 4 Panel C). Standard errors are bootstrapped using 1000 replications and reported in parentheses.

Panel A: Survival Expectations

	Application Rate			Approval Rate		
	All firms	Top 20 Banks	Community Banks/CUs	All firms	Top 20 Banks	Community Banks/CUs
Estimated PPP effect	5.81	5.54	0.86	1.73	0.55	2.88
	(1.90)	(0.93)	(1.14)	(1.90)	(0.93)	(1.14)
Adj R2	0.10	0.10	0.01	0.01	0.00	0.11
N	6137	2912	1512	3993	1958	957

Panel B: Employment

	Application Rate			Approval Rate		
	All firms	Top 20 Banks	Community Banks/CUs	All firms	Top 20 Banks	Community Banks/CUs
Estimated PPP effect	0.260	0.144	0.101	0.244	0.002	0.096
	(0.118)	(0.058)	(0.056)	(0.090)	(0.029)	(0.049)
Adj R2	0.059	0.102	0.004	0.069	0.000	0.070
N	6137	2912	1512	4571	2217	1083

Appendix Figures and Tables

Figure A1. This figure plots PPP application, approval, pending, and denial rates as of April 27, 2020 by firm owner demographics. The sample includes 1699 that report owner demographics.

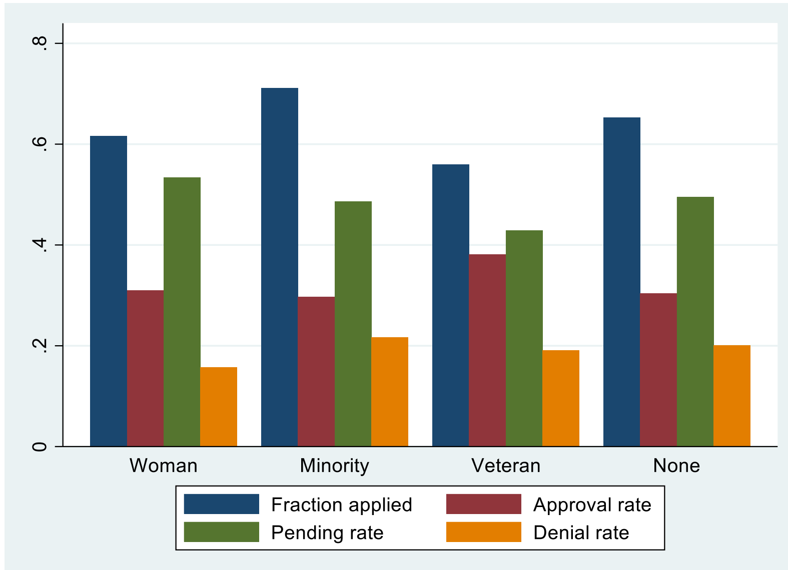


Figure A2. Approval rates by bank size and whether firm has a business account with bank. The sample includes 3993 firms that report expectations of surviving until December 2020 and Covid impact.

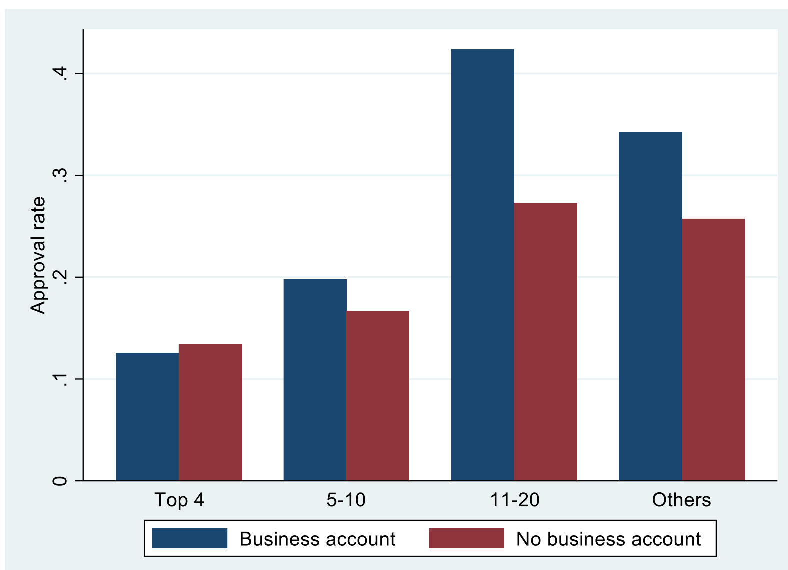


Figure A3. Approval rates by bank size and whether firm has an existing loan. The sample includes 3993 firms that report expectations of surviving until December 2020 and Covid impact.

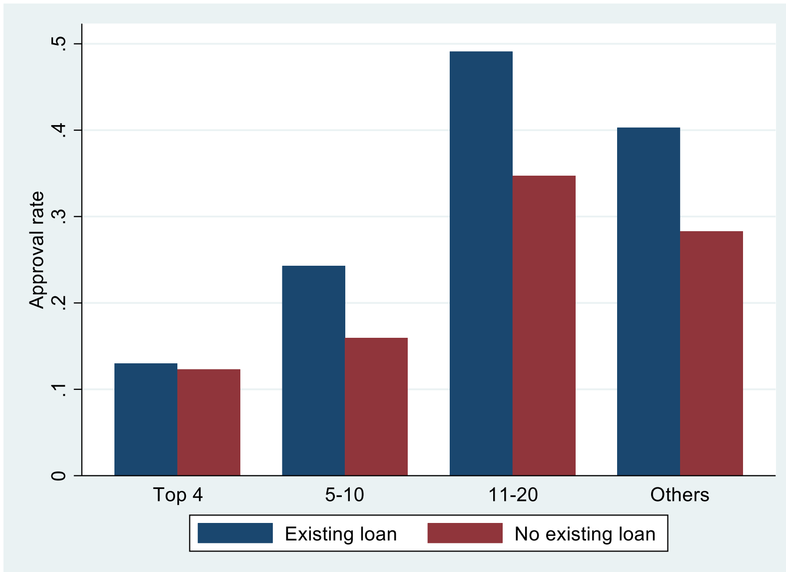


Figure A4. Approval rates by bank size and whether the owner knows a loan officer. The sample includes 3993 firms that report expectations of surviving until December 2020 and Covid impact.

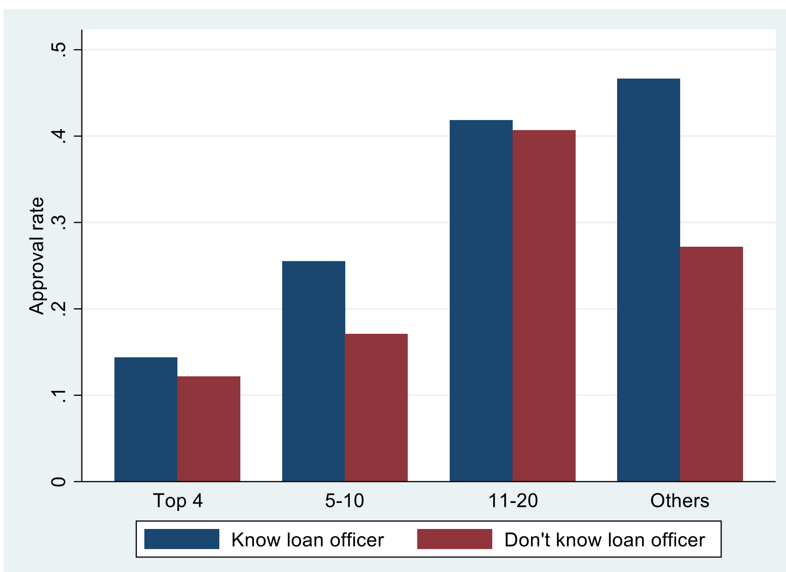


Figure A5. Approval rates by bank size for firms with low cash and large existing loans. The sample includes 127 such firms.

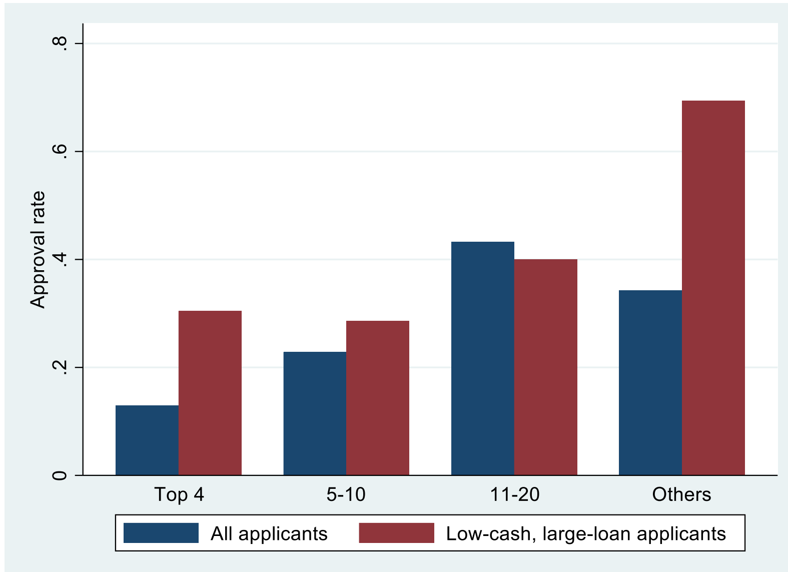


Table A1. Total PPP applications, approvals, and PPP loan amounts by bank size. This table reports aggregate statistics on PPP applications, approvals, and PPP loans amounts by bank size. For total applications and approvals, the sample includes 3993 firms that report expectations of surviving until December 2020 and Covid impact. Note that not all firms that report being approved for PPP report the size of the loan they receive. For total loan amounts and average loan amounts, the sample includes the 683 out of 995 approved firms that report loan amounts. Therefore, total dollars of loans approved are understated.

	Top 4	Top 5-10	Top 11-20	Others
Total PPP applications	1337	492	129	2035
Total approved PPP loans (#)	169	96	53	677
Total approved PPP loans ($m)	10.7	5.8	3.9	106.4
Average PPP loan size ($000)	124.8	82.2	114.9	215.9